Economics of Water Pollution: Permit Trading, Reliability of Pollution Control, and Asymmetric Information

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Dedication

To my forever loving family.

Abstract

This dissertation analyzes three aspects of the economics of water pollution and is organized in three essays. The first essay examines permit trading in water pollution where pollution is different in the persistence of environmental damage. The second essay examines the problem of reliably meeting a water quality standard under environmental uncertainty. The third essay considers the problem of reliably meeting a water quality standard under asymmetric information.

The first essay analyzes how to properly design water pollution permit trading with pollutants which are non-uniformly mixed across space and have different persistence in environmental damages. The efficient solution to water pollution abatement involves integrating the difference in the environmental persistence caused by pollutants and setting trading ratios in permit trading accordingly.

The second essay analyzes the problem of meeting a water quality standard with a certain degree of reliability given environmental stochasticity, where the distribution of environmental stochasticity is unknown. The essay develops the use of a reliability target that caps the probability of not attaining the target in any period at α, where $1 - \alpha$ is the level of reliability. A single-tailed version of Chebyshev's inequality is used that measures the maximum probability of being in the right tail of the probability distribution. The essay also examines a margin of safety in Total Maximum Daily Loads (TMDL) and concludes that if a given level of reliability is desirable, the margin of safety should vary with the level of TMDL.

The third essay considers the problem of reliably achieving a water quality standard where water pollution is generated by multiple sources and there is asymmetric information. Asymmetric information comes from privately observable actions like fertilizer application and private information on profits. This essay develops a Vickery-Clark-Groves (VCG) subsidy auction and incorporates a fine/reward scheme based on whether the water quality standard is met. This subsidy auction can achieve an efficient solution to the problem of achieving a reliability standard under asymmetric information.

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Chapter 1

Introduction

Water quality is an important dimension of water security. The deterioration of water quality directly affects human well-being: it threatens public health, degrades the recreational use of water bodies, and disturbs the provision of ecosystem services. For example, excessive mercury, arsenic, and nitrogen in drinking water damage human's kidney and liver, and affect oxygen transport in the bloodstream. Eutrophication caused by excessive nutrients makes water bodies unsuitable for fishing or swimming, and impairs nearby property values. Water-related ecosystem services, such as the capacity of assimilation, purification, and storage, may be undermined by water pollution, and people become more vulnerable to natural disasters.

The current state of water quality is not satisfactory. The United Nation reports that more than 80% of wastewater worldwide is discharged directly into surface waters without being collected or treated. In the European Union, agricultural pollution threatens 38% of water bodies (WWAP, 2015). In the United States, 49% of coastal and Great Lakes nearshore waters are rated poor in ecological fish tissue quality (USEPA, 2015). Nutrient pollution is widespread in lakes and rivers: 40% of lakes and 46% of rivers/streams are found with excessive total phosphorus, 35% of lakes and 41% of rivers/streams are found with excessive total nitrogen (USEPA, 2016a; USEPA, 2016b).

Considering a growing population, increasing urbanization, and economic development, the pressure on water quality may go up in coming decades. In order to serve the growing needs of populations and economies by 2050, food production should be doubled in developing countries, and 60% more food should be produced globally. We may see a trend of intensive and industrialized agriculture with improved crop productivity. However, more chemicals and fertilizers may be applied and end up in water bodies. Agricultural water pollution is likely to worsen.

The past decades have witnessed progress in protecting water quality. In the United States, the Environmental Protection Agency was established in 1970 to conserve the environment. The Federal Water Pollution Control Act, popularly known as the Clean Water Act, was passed in 1972 and is one of the most influential environmental laws. Moreover, there are continuing scientific studies on water pollution, in terms of its formation and causes, its consequences on human health and the environment, and related conservation practices or treatment techniques. Economists have studied non-market valuation of the deterioration of water quality, the optimal pollution control, and the development of policy instruments.

Despite the progress in protecting water quality, the incremental cost of controlling water pollution began to exceed the incremental benefit in the United States since around 1990 (Olmstead, 2009). One reason is increasing abatement cost due to inefficient environmental policies, such as technology-based uniform effluent standards (Shortle and Horan, 2013). The other reason is serious agricultural runoff which has not been regulated by the Clean Water Act. The lawsuit between the Des Moines Water Works (DMWW) and three Iowa drainage districts exemplifies a conflict between agriculture and water quality, where DMWW sued the districts for the excessive nitrates from the farmland into the Raccoon River, i.e. the source of drinking water for the Des Moines metro area. Controlling water pollution requires attentions, because the features of water pollution control should be properly considered in developing environmental policies and regulation.

The first feature of water pollution control is that water pollutants are non-uniformly mixed across space. The marginal environmental damage of water pollution differs with emission locations (Fisher-Vanden and Olmstead, 2013). Chapter 2 solves this non-uniform mixing problem of water pollution in permit trading, when there is a difference in persistence of environmental damage. Two types of pollution are discussed, with different persistence characteristics. One is flow pollution, which causes immediate but ephemeral environmental damage. The other is stock pollution, which generates persistent environmental damage. In solving the non-uniform mixing problem of water pollution, very few studies on permit trading have considered this difference between flow pollution and stock pollution. Ignoring this difference makes the first-best outcome of pollution control unattainable through permit trading. This chapter contributes to develop proper trading ratios in permit trading, which account for the dynamic process of stock pollution. They can induce the first-best outcome of pollution control.

The second feature of water pollution control is that the result of water pollution control is affected by environmental stochasticity. Given conservation management, water pollution may still be high in some years due to weather conditions like precipitation. Chapter 3 focuses on pollution control under environmental uncertainty, and emphasizes the importance of reliably meeting a water quality standard. This chapter proposes the use of a reliability target that caps the probability of not attaining the target in any period at α, where $1 - \alpha$ is the level of reliability. A single-tailed version of Chebyshev's inequality is used, which emphasizes preventing heavy pollution in the right tail of pollution probability when the probability distribution is unknown. The empirical results, using data from the Wolf Creek Watershed in Iowa, show that a reliability target results in larger losses of agricultural profits than an average target, but meets a specified water quality standard with a higher frequency. For example, a 75% loss in agricultural profit ($59.8 million) is incurred to achieve a 41% reduction in total nitrogen relative to the baseline pollution level with a 70% reliability, but this 41% reduction in total nitrogen is met in nine years during 2004-2013. It contrasts with the scenario of an average target, where this 40% reduction is only attained in five years during 2004-2013. The reliability target can be a valuable tool when it is important to meet a pollution reduction consistently. It should be properly considered in current water quality management.

The third feature of water pollution control is that asymmetric information widely exists to prevent deriving efficient pollution control. Abatement cost is private information, abatement practices are not observable, and individual pollution is too costly to detect. Chapter 4 looks at agricultural pollution control under asymmetric information. This chapter's contribution is to design a Vickery-Clark-Groves (VCG) subsidy auction and incorporate an ambient fine/reward scheme into the auction, so as to achieve reliability of pollution control under asymmetric information. This auction mechanism makes truthful revelation a dominant strategy. The fine/reward scheme prevents deviation from subsidized pollution abatement practices when they are unobservable.

Chapter 2

Water Quality Trading with Flow Pollution and Stock Pollution

2.1 Introduction

The success of permit trading in air pollution inspires people to extend its application in water pollution. Compared with air pollution, Fisher-Vanden and Olmstead (2013) summarize five challenges in forming a successful permit trading in water pollution. The first and foremost challenge is that compared with permit trading in air pollution, water pollutants are not uniformly mixed. Unlike air pollution, the marginal environmental damage of water pollution may differ to a large degree with the emission location (Fisher-Vanden and Olmstead, 2013). Considering the characteristics of receiving waters, we categorize water pollution into river pollution and lake pollution, or more generally, into flow pollution and stock pollution.

The difference between flow pollution and stock pollution is not just about the location of receiving waters, but more importantly, it is about the damage persistence. Flow pollution causes immediate damage but such damage does not persist in the environment, while stock pollution causes persisting damage in the environment. Depending on the decay rates and the characteristics of receiving waters, pollutants like chemicals, organisms and nutrients can generate both flow pollution and stock pollution. For example, chemicals and sediments deteriorate water quality both in the Grand River and in downstream Lake Michigan (Schrauben, 2010), and nutrients cause eutrophication problem in both the Mississippi River and the Gulf of Mexico. In most cases, river pollution is regarded as flow pollution, since pollutants are easily taken away by water flows, and their influence on a specific location along a river is temporary (Lieb, 2004).[1]

Lake pollution, on the other hand, can be properly considered as stock pollution, as pollutants may accumulate over time in a lake.

Back to the non-uniform mixing problem of water pollution in permit trading, location-related trading ratios have been developed, in the spirit of exchange rates, to account for the diverse impact of emissions from different locations. Actually, Montgomery (1972) in the seminal paper on market for pollution control discusses a trading-ratio system in permit trading. More recently, Farrow et al. (2005) develop another efficient trading-ratio system based on environmental damage of emissions from different places. Their trading-ratio system solves the non-uniform mixing problem of water pollution in an innovative way. More comprehensive factors such as heterogenous demographic conditions and economic development in distinct areas are considered in damage-based trading ratios, compared with effluent-based trading ratios more closely related to Montgomery's.

Although trading ratios are introduced for trade in non-uniformly mixed pollutants, the design of trading ratios has not completely considered the difference in persistence of environmental damage caused by pollutants. Many studies on water quality trading (WQT) only focus on river pollution, which is a form of flow pollution (e.g. Montgomery, 1972; Farrow et al., 2005; Hung and Shaw, 2005; Mesbah et al., 2009). Although there are some studies discussing some current permit trading programs which tend to alleviate deterioration in lakes and reservoirs, they look at physical effluents and do not take the dynamics of stock pollution damage into account (e.g. Stephenson et al., 1998; Obropta and Rusciano, 2006; Roberts and Clark, 2008). The coexistence of flow pollution and stock pollution has been, in general, either ignored, or treated as the same type of pollution in WQT.

Flow pollution and stock pollution require different models in analysis, as pointed out by Hoel and Karp (2001). Flow pollution fits a static model, while stock pollution needs

[1] We admit that not all pollutants are easily carried away by water flows. For example, phosphorus can be incorporated with sediments, which are insoluble and accumulating in rivers. In this sense, it is more like stock pollution than flow pollution. In the rest of paper, we focus on soluble pollutants which can be easily brought away to the downstream by water flows.

a dynamic model as pollutants accumulated in the past affect the current environmental damage. To our knowledge, these does not appear to be any research on WQT that considers persistent environmental damage of stock pollution. In designing trading ratios to solve the non-uniform mixing problem of water pollution, considering this difference between flow pollution and stock pollution is important in designing efficient WQT policies. Considering pollution control over stock pollution, there are numerous studies developing dynamic models and deriving the optimal solution and the steady state, whereas they have not analyzed whether it is possible to realize the cost-effective outcome via WQT (e.g. Dechert and O'Donnell, 2006; Iwasa et al., 2007; Laukkanen and Huhtala, 2008; Hediger, 2009).[2]

This paper contributes to solve the non-uniform mixing problem of water pollution, when there is heterogeneity in persistence of environmental damage. We develop a set of damage-based trading ratios in a scenario where both flow pollution and stock pollution are considered. In this paper, we point out that to solve the non-uniform mixing problem and attain the first-best result of pollution control, a set of trading ratios should consider marginal river damage, marginal lake damage, and the heterogeneity of persistence of environmental damage caused by polluters. In the simulation, we compare the equilibrium permit prices in the scenarios where persistence of environmental damage is considered or not. The efficiency loss could be high if we ignore the heterogeneity in persistence of environmental damage for pollution control.

The paper is organized in the following order. Section 2 establishes a cost-effective approach to pollution control from the perspective of the regulator. Section 3 analyzes the equilibrium of permit trading and develops damage-based trading ratios under the coexistence of flow pollution and stock pollution. Section 4 runs a simulation and compares the results of permit trading when the difference between flow pollution and stock pollution is considered and not. Section 5 concludes.

[2] In fact, the literature on WQT does not lack dynamic optimization analysis. There is an increasing number of studies on dynamic permit trading since 1996, where the dynamic process occurs as a result of permit banking becoming possible in tradable permit programs (Hasegawa and Salant, 2015). These studies use optimal control theory and analyze the time path of pollution and permit prices as well as decentralized behavior of polluters (e.g. Rubin, 1996; Cronshaw and Kruse, 1996). However, this dynamic process is not relevant to the dynamic environmental damage of stock pollution that we discuss here. In this paper, we do not consider permit banking in WQT.

2.2 Cost-Effectiveness Problem

Suppose that the regulator intends to control pollution in both a river and a receiving lake. We index relevant polluters by $i = 1, 2, ..., n$ from the upstream to the downstream of the river, and the nth polluter locates closest to the lake. The pollutant flows to the downstream, and its decay rate in the lake is γ. This decay rate tells how much of the pollutant remains in the lake one period later, and is determined by physicochemical properties of the pollutant and the aquatic ecosystem. The discount rate r describes monetary depreciation in one period. A set of transfer coefficients is introduced to capture how much of the pollutant from polluter i, after decaying and being assimilated in the river, ends up arriving at polluter j. We denote this transfer coefficient as τ_{ij} with $\tau_{ij} \leq 1$.[3] We further denote the transfer coefficient to the lake as τ_{is}. If the nth polluter is located at the lake, then $\tau_{ns} = 1$. The unregulated emission level of polluter i is e_i^0, and the initial pollutant stock in the lake is S_0. The pollutant stock in the lake at time t is $S(t)$. Polluter i's abatement effort at time t is $a_i(t)$, and its abatement cost is $C_i\left(a_i(t)\right)$. Assume that abatement costs of all polluters are strictly increasing and strictly convex in abatement.

We assume that environmental damage caused by flow pollution (which will be referred to as river damage) and stock pollution (which will be referred to as lake damage) are both linear in concentration, so that polluters have constant marginal impact on the environment. Denote d_i as the environmental damage coefficient of river damage caused by the emission from polluter i, measured in dollar per unit of the pollutant. This coefficient integrates all downstream environmental damage caused by polluter i. In this sense, polluter i generates river damage $D_i(t)$ at time t, where

[3] Farrow et al. (2005) describe how to compute transfer coefficients in the river. They first calculate the pollutant concentration C (mg/L) at distance n (m) downstream from a pollution location i:

$$C_{ni} = \frac{e_i}{Q} \mathrm{e}^{-k\theta^{(T-20)} \frac{n}{U}},$$

where e_i (kg/day) is the discharge rate at the location i, Q (m^3/day) is the stream flow, k (day^{-1}) is the nominal decay rate, θ is the sensitivity coefficient of k to a temperature T (Celsius), and U (meters/day) is the stream velocity. They then compute the transfer coefficient between the location i and the location j using: $\tau_{ij} = \frac{C_{ji}}{C_{0i}}$.

This transfer coefficient can be improved by including the time effect of the pollutant moving from the location i to the location j. The modified transfer coefficient is $\tau_{ij}\mathrm{e}^{-rq}$, where r is the discount rate, and q is the average time which takes the pollutant to flow from the location i to the location j.

$D_i(t) = d_i(e_i^0 - a_i(t))$. The environmental damage coefficient of lake damage is δ, and $\delta S(t)$ stands for the lake damage at time t. Lake damage depends on the pollutant stock, not flow. Although using a nonlinear function to describe environmental damage appears more precise (e.g. Dechert and O'Donnell, 2006; Laukkanen and Huhtala, 2008), a linear functional form for environmental damage is also common in the literature.[4]

Besides, Kolstad (1996) finds that damage of some pollutants like greenhouse gas is quite linear over a fairly broad range of the current stock. Also, a significant linear relationship may exist between some pollutants, like arsenic and heavy metal, and their effect on health consequences (Mazumder, 2005; Ergene et al., 2007).

1. Flow Pollution Only

Following Farrow et al. (2005), we start with a cost-effectiveness problem of flow pollution in which stock pollution is not considered. The regulator attempts to minimize total abatement cost subject to a constraint $\bar{D}$ on river damage in each period t. The problem is below:

$$\begin{aligned} &\min_{\{a_1(t),a_2(t),...,a_n(t)\}} \sum_{i=1}^{n} C_i(a_i(t)) \\ &s.t. \quad \sum_{i=1}^{n} d_i \left(e_i^0 - a_i(t)\right) \leq \bar{D}_F, \\ &a_i(t) \geq 0, \forall i \in \{1,2,...,n\}. \end{aligned} \tag{A}$$

Farrow et al. (2005) solve this problem and find that the marginal cost to reduce river damage is equal everywhere in the solution to the problem above. The corresponding least-cost marginal cost ratio is:

$$\frac{C_i'(a_i^*(t))}{C_j'(a_j^*(t))} = \frac{d_i}{d_j}, \quad \forall i,j \in \{1,2,...,n\}. \tag{2.1}$$

2. Stock Pollution Only

We continue with a cost-effectiveness problem of stock pollution in which flow pollution is not considered. Regarding persistent environmental damage of lake pollution, the regulator limits the discounted total lake damage over time to $\bar{D}_S$. The pollutant accumulates according to the state equation: $\dot{S}(t) = -\gamma S(t) + \sum_{i=1}^{n} \tau_{is} \left(e_i^0 - a_i(t)\right)$.

[4] To name a few examples: Ribaudo et al. (1994), Hoel and Schneider (1997), Baudry (2000), Parry et al. (2003), Matsueda et al. (2006), Dellink et al. (2008), Masoudi et al. (2015)

The problem is below:

$$
\begin{aligned}
&\min_{\{a_1(t),a_2(t),...,a_n(t)\}} \int_0^{+\infty} \mathrm{e}^{-rt} \sum_{i=1}^{n} C_i(a_i(t))\ \mathrm{d}t \\
&s.t.\quad \dot{S}(t) = -\gamma S(t) + \sum_{i=1}^{n} \tau_{is} \left(e_i^0 - a_i(t)\right), \\
&\int_0^{+\infty} \mathrm{e}^{-rt} \delta S(t)\ \mathrm{d}t \leq \bar{D}_S, \\
&a_i(t) \geq 0, \forall i \in \{1, 2, ..., n\}.
\end{aligned} \tag{B}
$$

The integrand function in the objective is strictly convex. The feasible set of the problem is closed and bounded. The pollutant stock is also bounded for all admissible pairs across time. By the Filippov-Cesari Existence Theorem, a solution to Problem C always exists. Mangasarian conditions also ensure that this solution is unique. The most rapid approach path can achieve the optimality of this problem, where the solution in the steady state is available in the appendix. The least-cost marginal cost ratio in the steady-state solution to this cost-effectiveness problem is:

$$
\frac{C_i'(a_i^*(t))}{C_j'(a_j^*(t))} = \frac{\tau_{is}}{\tau_{js}}, \quad \forall i, j \in \{1, 2, ..., n\}. \tag{2.2}
$$

3. Flow Pollution and Stock Pollution

Given the analysis above, it is relatively easy to derive the solution to a cost-effectiveness problem, where the regulator aims at both flow pollution and stock pollution. A constraint $\bar{D}$ is imposed on the discounted total environmental damage of both river pollution and lake pollution over time (which will be referred to as total damage). The regulator solves the following problem:

$$
\begin{aligned}
&\min_{\{a_1(t),a_2(t),...,a_n(t)\}} \int_0^{+\infty} \mathrm{e}^{-rt} \sum_{i=1}^{n} C_i(a_i(t))\mathrm{d}t \\
&s.t.\quad \dot{S}(t) = -\gamma S(t) + \sum_{i=1}^{n} \tau_{is} \left(e_i^0 - a_i(t)\right), \\
&\int_0^{+\infty} \mathrm{e}^{-rt} \left(\sum_{i=1}^{n} D_i + \delta S(t) \right) \mathrm{d}t \leq \bar{D}, \\
&D_i(t) = d_i \left(e_i^0 - a_i(t)\right), \forall i \in \{1, 2, ..., n\} \\
&a_i(t) \geq 0, \forall i \in \{1, 2, ..., n\}.
\end{aligned} \tag{C}
$$

The most rapid approach path can achieve the optimality of this problem. Solving the first-order conditions, the marginal cost to diminish the total damage, is the same everywhere in the steady-state solution to the problem above. The marginal cost ratio in the steady-state solution is:

$$\frac{C_i'(a_i^*(t))}{C_j'(a_j^*(t))} = \frac{d_i + \dfrac{\delta}{r+\gamma}\tau_{is}}{d_j + \dfrac{\delta}{r+\gamma}\tau_{js}}, \quad \forall i, j \in \{1, 2, ..., n\}. \tag{2.3}$$

The marginal cost ratios in the equations (2.1)-(2.3) reflect the relationship of steady-state abatement efforts among polluters in the cost-effective solutions to Problem (A)-(C) respectively, where Problem (A) only considers flow pollution, Problem (B) only considers stock pollution, and Problem (C) considers both.

2.3 Water Quality Trading

Water quality trading is a market-based instrument for pollution control, where polluters can trade permits with each other. The possession of these permits endows polluters with the right to discharge a certain level of emission. The initial allocation of permits to polluters is $\bar{\boldsymbol{l}} = (\bar{l}_1, \bar{l}_2, ..., \bar{l}_n)$. Polluters can also create permits by their pollution abatement.[5] Given that water pollutant is not uniformly mixed, permits of different polluters cannot be traded on a one-to-one basis. Trading ratios are introduced to solve the non-uniform mixing problem in WQT. The ratios are akin to exchange rates of permits among individual polluters. Denote the trading ratio between polluter i and polluter j as κ_{ij}. Taking $\kappa_{ij} = 2$ as an example, it means that one permit of polluter j allows polluter i to discharge two times as much of the pollutant as polluter j. Or, put the other way, one permit of polluter i grants polluter j the right to emit half as much as polluter j does. In the regulatory framework of WQT, trading ratios and the amount of permits are exogenously determined by the regulator.

Assuming that there is no permit banking or borrowing in WQT, each polluter faces

[5] In some literature, when a permit is created by reducing pollution, it is called "credit" which is tradable in permit trading, too.

the following problem each period:

$$
\begin{aligned}
&\min_{r_{ki},r_{si},r_{ji}} C_i(a_i) - p_i r_{si} + \sum_{j\neq i} p_j r_{ji} \\
&s.t. \quad \left(e_i^0 - r_{ki}\right) - \sum_{j\neq i} \kappa_{ji} r_{ji} \leq 0, \\
&\qquad r_{si} + r_{ki} = \bar{l}_i + a_i, \\
&\qquad r_{ki}, r_{si}, r_{ji} \geq 0, \forall i \in \{1, 2, ..., n\},
\end{aligned} \tag{D}
$$

where r_{si} is the permits sold by polluter i, r_{ki} is the permits kept by polluter i, r_{ji} is the permits that polluter i purchases from polluter j, and p_i is the price on permit of polluter i.

An equilibrium in the permit-trading market is defined as follows: Given a matrix of trading ratios $\boldsymbol{\kappa}$ and the amount of permits to polluters $\bar{\boldsymbol{l}}$, an equilibrium in the a permit market is a vector of permit prices $\boldsymbol{p}$, a vector of polluters' abatement $\boldsymbol{a}$ and a sequence of trading activities $\{r_{si}, \{r_{ji}\}_{j\neq i}\}_{i=1}^n$, where (i) $\boldsymbol{a}$ and $\{r_{si}, \{r_{ji}\}_{j\neq i}\}_{i=1}^n$ solve Problem (D) for every polluter, and (ii) $\sum_{i\neq j} r_{ji} \leq r_{sj}$ for every polluter $j \in \{1, 2, ..., n\}$ and the equality holds when $p_j > 0$. Because the feasible set of Problem (D) is compact, the objective function is continuous and convex in abatement and linear in trading activities, permit-trading equilibrium always exists. Although this equilibrium is not necessarily unique, as the trading activities $\{r_{si}, \{r_{ji}\}_{j\neq i}\}_{i=1}^n$ could have multiple combinations, the abatement vector $\boldsymbol{a}$ is unique in the equilibrium.[6] Assuming there is no permit banking or borrowing, the abatement levels and the marginal cost ratio in the equilibrium at time t are:

$$
\begin{aligned}
&a_i^{**}(t) = C_i^{'-1}(p_i(t)), \quad \forall i \in \{1, 2, ..., n\}, \\
&\frac{C_i'(a_i^{**}(t))}{C_j'(a_j^{**}(t))} = \kappa_{ij}(t), \quad \forall i, j \in \{1, 2, ..., n\}.
\end{aligned} \tag{2.4}
$$

2.3.1 Trading Ratios

Trading ratios and the initial endowment of permits are critical in an equilibrium of a permit market. They also determine whether the cost-effective outcome of pollution control is achievable in WQT. Given that the abatement vector is unique both

[6] The first-order conditions of Problem (D) have $n^2 + 2n$ unknowns and $\left(n^2 + 5n\right)/2$ non-identical equations, so the solution $\{a_i, r_{si}, \{r_{ji}\}_{j\neq i}\}_{i=1}^n$ is not unique for $n \geq 3$.

in the solution to a cost-effectiveness problem of pollution control and in permit-trading equilibrium, we focus on the steady-state trading ratio here, which should be $\kappa_{ij}(t) = C_i'(a_i^*(t))/C_j'(a_j^*(t))$ to attain the cost-effective outcome. In the following, we want to show that by setting κ_{ij} in this way, the net change of environmental damage induced by permit trading in the steady state is zero, and the total amount of permits can be appropriately determined under different limits on environmental damage of water pollution.

Suppose, for example, that there are two polluters in WQT at time t, and polluter i purchases permits from polluter j. Polluter i, having obtained these permits, can now emit additional discharge $\Delta e_i(t)$, while polluter j forgoes these permits so he must generate additional abatement $\Delta a_j(t)$. The ratio between $\Delta a_j(t)$ and $\Delta e_i(t)$ is the trading ratio κ_{ij}.

1. Flow Pollution Only

We first begin with WQT which focuses only on flow pollution. The change in the river damage during permit trading in every period t is:

$$\Delta D_F(t) = d_i \Delta e_i(t) - d_j \Delta a_j(t).$$

By setting $\kappa_{ij}(t)$ equal to the least-cost ratio in (2.1), any set of permissible trades will lead to $\Delta D_F(t) = 0$. The contemporary incremental river damage in a permit market at time t is offset. The cost-effective outcome of pollution control over river pollution can be achieved through WQT (Farrow et al., 2005). The proper trading ratio and the amount of permits at time t are below:

$$\begin{aligned} \kappa_{ij}(t) &= \frac{d_i}{d_j}, \quad \forall i, j \in \{1, 2, ..., n\}, \\ \sum_{i=1}^{n} d_i \bar{l}_i(t) &\leq \bar{D}_F, \end{aligned} \tag{2.5}$$

where $\bar{D}_F$ is the constraint on the river damage per period.

2. Stock Pollution Only

We continue with WQT which looks only at stock pollution, without considering flow pollution. The effect of stock pollution on the environment persists over time. At time t, the additional emission $\Delta e_i(t)$ and the additional abatement $\Delta a_j(t)$ also influence the path of the pollutant stock over time. Denote the impact of $\Delta e_i(t)$ on the instantaneous change of the pollutant stock as $\Delta S(e_i(t), t)$. Similarly, denote the impact of $\Delta a_j(t)$ on the instantaneous change of the pollutant stock as $\Delta S(a_j(t), t)$. The increment in the discounted lake damage over time is:

$$\Delta D_S = \int_0^{+\infty} e^{-rt} \delta \Delta S(e_i(t), t) \text{ d}t - \int_0^{+\infty} e^{-rt} \delta \Delta S(a_j(t), t) \text{ d}t.$$

When $\kappa_{ij}(t)$ is set to the cost-effective marginal cost ratio in (2.2), any set of permissible trades will lead to $\Delta D_S = 0$. The continuous incremental damage over time is offset. We can set trading ratios and the initial endowment of permits at time t as follows, and the cost-effective outcome of pollution control will be achieved:

$$\begin{aligned} &\kappa_{ij}(t) = \frac{\tau_{is}}{\tau_{js}}, \quad \forall i, j \in \{1, 2, ..., n\}, \\ &\sum_{i=1}^{n} \frac{\delta}{r+\gamma} \tau_{is} \bar{l}_i(t) \leq \left(\bar{D}_S - \frac{\delta S_0}{r+\gamma} \right) r, \end{aligned} \tag{2.6}$$

where S_0 is the initial lake pollutant stock, and $\bar{D}_S$ is the limit on the discounted total lake damage.

3. Flow Pollution and Stock Pollution

Given the discussion above, we can now analyze WQT that targets both flow pollution and stock pollution. The change in the discounted total damage is:

$$\Delta D = d_i \Delta e_i(t) + \int_0^{+\infty} e^{-rt} \delta \Delta S(e_i(t), t) \text{ d}t - d_j \Delta a_j(t) - \int_0^{+\infty} e^{-rt} \delta \Delta S(a_j(t), t) \text{ d}t.$$

When $\kappa_{ij}(t)$ equals the optimal marginal cost ratio in (2.3), any permissible set of trades will lead to $\Delta D = 0$. An increase in the discounted total damage is cancelled out by a decrease in the discounted total damage during permit trading. The following trading ratios and the endowment of permits can attain the cost-effective outcome of pollution control over flow pollution and stock pollution:

$$\begin{aligned} &\kappa_{ij}(t) = \frac{d_i + \dfrac{\delta}{r+\gamma}\tau_{is}}{d_j + \dfrac{\delta}{r+\gamma}\tau_{js}}, \quad \forall i, j \in \{1, 2, ..., n\}, \\ &\sum_{i=1}^{n} \left(d_i + \frac{\delta}{r+\gamma} \tau_{is} \right) \bar{l}_i(t) \leq \left(\bar{D} - \frac{\delta S_0}{r+\gamma} \right) r, \end{aligned} \tag{2.7}$$

where $\bar{D}$ is the upper bound on the discounted total damage. Based on the analysis above, we can summarize that:

Conclusion 1. *Suppose a river flows into a lake, and a pollutant causes damage both in the river and the lake. Environmental damage of flow pollution and of stock pollution are linear in concentration. Water quality trading can achieve the cost-effective outcome of pollution control. Regarding different aims of the regulator, whether to protect the river, the lake or both, the proper trading ratio and the proper vector of permits are specified in* (2.5)*,* (2.6)*, and* (2.7) *respectively.*

2.3.2 Interaction Between Flow Pollution And Stock Pollution

Environmental damage caused by flow pollution and stock pollution is not necessarily the same in its degree of severity. Stock pollution is determined by the pollutant stock, where the initial stock and the decay rate of the pollutant play an important role, while flow pollution depends merely on the pollutant flow. A certain level of reduction in the discharge from polluters may be sufficient to achieve a given level of water quality in the river, but not sufficient to solve water deterioration in the lake if the initial pollutant stock is high. When considering the entire water system, the degree of heterogeneity in environmental damage might be even greater.

In a combined river-lake system, the regulator tends to have multiple constraints on the river damage and the lake damage, rather than a single constraint on the total damage. Take the eutrophication problem of the Mississippi River and the Gulf of Mexico as an example. The Mississippi River carries millions of tons of nutrients into the Gulf of Mexico every year, causing the "dead zone" around the Gulf. There is an established target of 45% reduction in riverine total nitrogen and riverine total phosphorus to solve this stock pollution in the Gulf of Mexico. To meet this target, the United States Federal government has been prompted to carry out a Gulf Hypoxia Action Plan covering all watersheds upstream. Regardless of this Action Plan, the state governments of, for example, the Upper Mississippi River watershed such as Minnesota, Iowa and Illinois, may have additional pollution control targets for water quality of their local rivers. In this sense, the social cost-effectiveness problem still focuses on both flow pollution and stock pollution, but has separate constraints on environmental damage caused by these two types of pollution. We describe the problem as follows:

$$\min_{\{a_1(t),a_2(t),...,a_n(t)\}} \int_0^{+\infty} \mathrm{e}^{-rt} \sum_{i=1}^{n} C_i(a_i(t))\mathrm{d}t$$
$$s.t. \quad \dot{S}(t) = -\gamma S(t) + \sum_{i=1}^{n} \tau_{is} \left(e_i^0 - a_i(t)\right),$$
$$\sum_{i=1}^{n} d_i \left(e_i^0 - a_i(t)\right) \leq \bar{D}_F, \qquad \int_0^{+\infty} \mathrm{e}^{-rt} \delta S(t)\mathrm{d}t \leq \bar{D}_S, \tag{D}$$
$$a_i(t) \geq 0, \forall i \in \{1, 2, ..., n\}.$$

where $\bar{D}_F$ is the limit on the river damage in each period, and the $\bar{D}_S$ is the limit on the discounted lake damage over time.

Solving the cost-effectiveness problem of pollution control under the two constraints above, we will have the following marginal cost ratio:

$$\frac{C_i'(a_i^*(t))}{C_j'(a_j^*(t))} = \frac{\bar{\lambda}_F d_i + \dfrac{\bar{\lambda}_S \delta}{r+\gamma}\tau_{is}}{\bar{\lambda}_F d_j + \dfrac{\bar{\lambda}_S \delta}{r+\gamma}\tau_{js}}, \quad \forall i, j \in \{1, 2, ..., n\}, \tag{2.8}$$

where $\bar{\lambda}_F$ is the Lagrange multiplier of the river damage constraint and $\bar{\lambda}_S$ is the Lagrange multiplier of the lake damage constraint. If one of the constraints is slack, the problem degenerates to a prior problem discussed already in this paper. Compared with the marginal cost ratio in the scenarios when there is a single constraint on environmental damage, the ratio here contains $\bar{\lambda}_F$ and $\bar{\lambda}_S$. To properly figure out $\bar{\lambda}_F$ and $\bar{\lambda}_S$, we need to know the abatement cost information of polluters. Given the analysis above, we summarize:

Conclusion 2. *Suppose a river flows into a lake, and a pollutant causes damage both in the river and the lake. Environmental damage of flow pollution and of stock pollution are both linear. Water quality trading can achieve the cost-effective outcome of pollution control when there are separate constraints on environmental damage caused by flow pollution and stock pollution. However, it requires complete information on polluters' abatement costs to figure out the proper trading ratios as specified in (2.8), and the permits* $\sum_{i=1}^{n} \left(\bar{\lambda}_F d_i + \frac{\bar{\lambda}_S \delta}{r+\gamma}\tau_{is}\right) \bar{l}_i(t) \leq \left(\bar{D} - \frac{\bar{\lambda}_S \delta S_0}{r+\gamma}\right) r$*, where* $\bar{D} = \bar{\lambda}_F \bar{D}_F + \bar{\lambda}_S \bar{D}_S$*.*

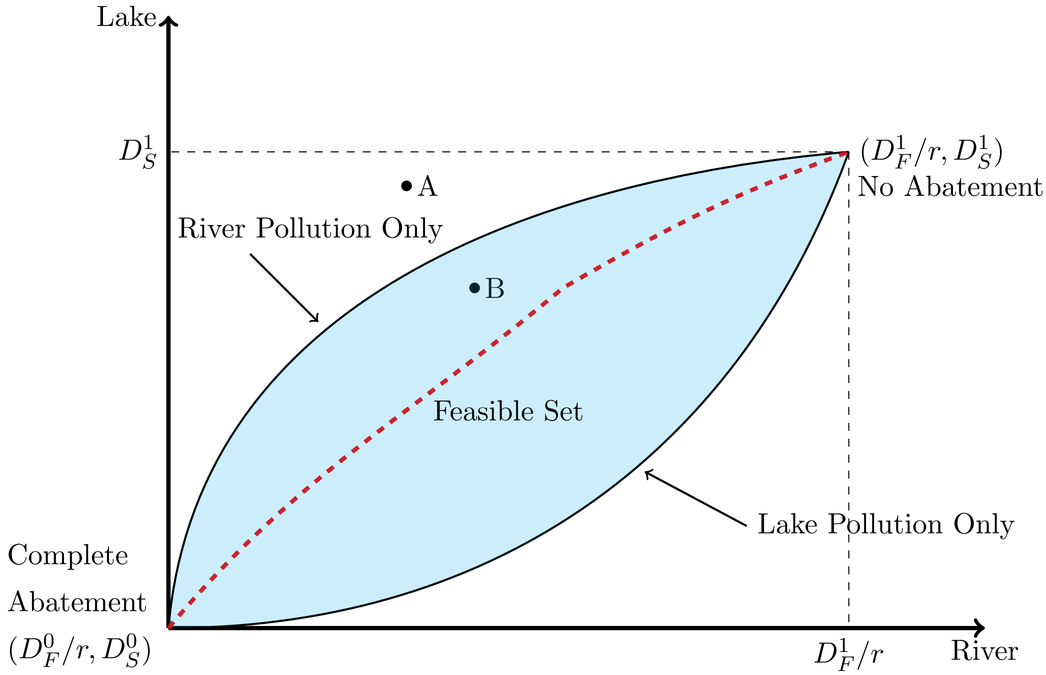


Figure 2.1: Correlation between River Damage and Lake Damage

Environmental damage caused by flow pollution and stock pollution is interconnected. In this paper, the river and the lake are linked, so a change in riverine water quality moves together with a change in lake water quality. Figure 2.1 shows all possible combinations of flow pollution and stock pollution, as indicated by the blue area. In the figure, D_S^0 and D_S^1 are the lower and the upper bounds of the discounted lake damage over time respectively, D_F^0/r and D_F^1/r are the lower and the upper bounds of the discounted river damage over time. When the regulator only focuses on controlling river pollution, the result of WQT will appear at a point on the upper curve from $(D_F^0/r, D_S^0)$ to $(D_F^1/r, D_S^1)$ in Figure 1. When the regulator only looks at lake pollution, the result of WQT will come up at a point on the lower curve in the figure. Moreover, if the constraints $\bar{D}_S$ and $\bar{D}_F/r$ are set outside the blue area, for example, at the point A, at least one of the constraints is redundant. If the constraints $\bar{D}_S$ and $\bar{D}_F/r$ are given inside the blue area, for example, at the point B, complete cost information on polluters is needed to arrive at this point in efficient permit trading. The dashed curve in the figure displays the possible combinations of river damage and lake damage when there is a single target at the total damage. If B sits further above this dashed curve, $\bar{D}_F$ will become more stringent to achieve than $\bar{D}_S$, and the ratio of $\bar{\lambda}_F/\bar{\lambda}_S$ will be higher. The corresponding marginal cost ratio and total abatement cost in the optimal solution to achieve B will approach to the ones which only focus on the river damage.

2.3.3 Further Consideration on Stock Pollution

The distinction between flow pollution and stock pollution lies in persistence of their environmental damage, and should be considered in solving the non-uniform mixing water pollution problem. This non-uniform mixing problem occurs due to a large degree of diversity in the marginal environmental damage caused by the discharge from different locations. The area being affected, the physicochemical properties of pollutants and the duration of environmental damage all depend on this diversity. In this sense, if we do not consider the difference between flow pollution and stock pollution in persistence of environmental damage, we will fail to properly solve the non-uniform mixing problem of water pollution in permit trading.

Stock pollution can appear in many other forms in practice, besides lake contamination. For example, groundwater contamination also belongs to stock pollution, as pollutants accumulate in groundwater which consistently affect drinking water quality as well as soil quality. However, the public have not paid attention to the environmental damage caused by groundwater contamination as well as the expensive treatment cost of groundwater pollutants until recently. In cooperation with EPA, New England Interstate Water Pollution Control Commission (2001) educates K-12 students in protecting water, and mentions that "(f)or too long, our ground water resources have been out of sight and out of mind, as is often the case, our wake-up call has come in the form of accumulated ground water pollution crises."

Considering multiple sources of stock pollution, it is possible that tradable permit programs in practice may either ignore the existence of stock pollution or do not consider persistence of environmental damage caused by stock pollution. For example, some tradable permit programs tend to consider only transfer coefficients and the uncertainty between sellers and buyers, in designing trading ratios, without regard to the discount rate and the initial pollutant stock in terms of stock pollution. Some trading programs even use uniform trading ratios, neglecting the location of polluters (Ohio Environmental

Protection Agency, 2007; Minnesota Pollution Control Agency, 2011; Corrales et al., 2013; Kellre et al. 2014).

We may also consider the case in which a regulator controls the instantaneous water quality in the river and the lake, but fail to account for persistence of pollutant in the lake in this case. The wrong cost-effectiveness problem will be:

$$\begin{aligned} &\min_{\{a_1(t),a_2(t),\ldots,a_n(t)\}} \sum_{i=1}^{n} C_i(a_i(t)) \\ s.t. \quad &\sum_{i=1}^{n} d_i\left(e_i^0 - a_i(t)\right) + \delta S(t) \leq \bar{D}, \\ &S = \sum_{i=1}^{n} \tau_{is}\left(e_i^0 - a_i(t)\right), \\ &a_i(t) \geq 0, \forall i \in \{1,2,...,n\}. \end{aligned} \tag{E}$$

The corresponding "efficient" trading ratio to achieve the least-cost outcome of Problem (E) is:

$$\kappa_{ij}(t) = \frac{d_i + \delta\tau_{is}}{d_j + \delta\tau_{js}}, \forall i,j \in \{1,2,...,n\}. \tag{2.9}$$

Compared with the cost-effective trading ratio in (2.3), the decay rate γ and the discount rate r are missing here. This is because the regulator does not account for the dynamic process and the continuous environmental damage of stock pollution when establishing permit trading. Unless $r+\gamma=1$ or $\tau_{is}=0$, $\forall i \in \{1,2,...,n\}$, this trading ratio cannot lead to the cost-effective outcome of pollution control. If $r+\gamma=1$, the continuous environmental damage of stock pollution in the next period will vanish after discounting and pollutant decay. Consider the case in which $\gamma=0$ and $r=1$. In this case, although the pollutant lasts forever in the lake, the discounted lake damage over time equals its damage in the current period, because people are all extremely impatient. The influence of stock pollution is essentially the same as that of flow pollution. If $\tau_{is}=0$, $\forall i \in \{1,2,...,n\}$, then polluters are so far upstream along the river that the amount of the pollutant arriving at the lake is trivial. Given the analysis above, we summarize:

Conclusion 3. *Suppose a river flows into a lake, and a pollutant causes damage both in the river and the lake. Environmental damage of flow pollution and of stock pollution are both linear. If the regulator solves both flow pollution and stock pollution, but does not account for persistence of environmental damage in the lake, water quality* *trading will not arrive at the cost-effective outcome of pollution control, unless* $r+\gamma=1$ *or* $\tau_{is}=0$, $\forall i\in\{1,2,...,n\}$.

2.4 Simulation

This section presents results of a simulation on permit trading in a segment of the Ohio River, when the difference between flow pollution and stock pollution is or is not considered. In the simulation, all polluters in the permit-trading system are located along the river, and their emissions can be monitored. In the rest of this section, we will clarify the assumption and the parameters used in the simulation, and then analyze the results of permit trading under different scenarios.

We assume a homogeneous abatement cost function for every polluter. A heterogenous abatement cost function is not necessary for permit trading to occur here. The form of this cost function is:

$$C(a_i)=\alpha+\beta a_i+\xi\left(e^0-a_i\right)\ln\left(1-\frac{a_i}{e^0}\right),$$

where e^0 is the unregulated emission level, α is the fixed cost of abatement, $\alpha\geq 0$, $\beta>0$, $\xi>0$, and $\beta>\xi$. The marginal cost is strictly positive and infinitely large for complete abatement.

Although the values of environmental damage coefficients are assumed here, we think it worthwhile to discuss the method of computing these values if there is empirical data. It will help understand the meaning of these coefficients. The environmental damage coefficient of flow pollution d_i (which will be referred to as river damage coefficient) integrates all the marginal environmental damage over the downstream area of the river. This coefficient is related to the size of downstream area, the transfer coefficients of pollutants, the influence on public health and the economy attributed by pollutants, and other relevant factors. Farrow et al. (2005) describe the river damage coefficient as follows:

$$d_i=\sum_{k=0}^{m}\omega\cdot h_k\cdot\tau_{ik}\cdot\frac{1}{Q_{0i}},$$

where m is the total amount on stream segments downstream of polluter i, ω ($\$\cdot(\text{kg}/m^3)^{-1}$) is the marginal value of a change in riverine water quality and is measured by willingness-to-pay of a resident for an improvement in riverine water quality, h_k is the number of residents being affected by river pollution in the kth stream segment, Q_{0i} (m^3/day) is the stream flow at polluter i, τ_{ik} is the transfer coefficient from polluter i to the kth stream segment. The location of polluter i is defined as the 0th stream segment. The environmental damage coefficient of stock pollution (also referred to as lake damage coefficient), can be derived in a similar way:[7]

$$\delta = \sum_{k=1}^{m} \omega \cdot h_k \cdot \frac{1}{Q_s},$$

where m is the total number of the segments around the lake, ω ($\$ \cdot (\mathrm{kg}/m^3)^{-1}$) is the willingness-to-pay of a resident for an improvement in water quality of the lake, h_k is the number of residents being affected by lake pollution in the kth segment, and Q_s (m^3) is the volume of water in the lake.

The parameters in the simulation are presented in Table 2.1. Taking advantage of the empirical example in the Farrow et al. (2005) based on the total sewer overflow in the Upper Ohio River Basin, we directly take their values on the river damage coefficients (with the coefficient on Clairton, Pennsylvania being normalized to one) and also their unregulated emission levels. The transfer coefficients to the lake are assumed sequentially downstream. The other parameters are assumed to take the values below unless specified.

[7] According to the definition of the lake damage coefficient, we have:

$$\delta = \sum_{k=1}^{m} \|\frac{\partial V(W,h_k)}{\partial S}\| = \sum_{k=1}^{m} \|\frac{\partial V(W,h_k)}{\partial W}\frac{\partial W}{\partial C_k}\frac{\partial C_k}{\partial S}\| = \sum_{k=1}^{m} \|(\omega \cdot h_k)\cdot(-1)\cdot\frac{1}{Q_{ks}}\|,$$

where $V(\cdot)$ is the benefit function of water quality improvement which depends on water quality W and the population of residents h_k. The derivative of water quality with respect to the pollutant concentration C_k in the kth segment is assumed -1 uniformly in the lake damage coefficient.

Table 2.1: Parameters in the Simulation on Permit Trading

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
d_1	1.62 (\$/kg)	τ_{1s}	0.10	δ	5 (\$/kg)
d_2	2.21 (\$/kg)	τ_{2s}	0.15	r	0.05
d_3	1.00 (\$/kg)	τ_{3s}	0.20	γ	0.40
d_4	0.38 (\$/kg)	τ_{4s}	0.25	e^0	231 (kg)
d_5	3.99 (\$/kg)	τ_{5s}	0.30	S_0	10 (ton)
d_6	0.36 (\$/kg)	τ_{6s}	0.35	α	100
d_7	1.40 (\$/kg)	τ_{7s}	0.40	β	1
d_8	0.03 (\$/kg)	τ_{8s}	0.45	ξ	1

Given that all polluters in the simulation have the same abatement cost functions, their contribution to pollution control in an efficient solution primarily depends on their environmental damage coefficients. In the absence of a regulation, the river damage in every period is \$2,538, and the discounted lake damage over time is \$224,040. When the regulator aims at, for example, a 30% reduction in the river damage, polluter 5, in a cost-effective solution, must abate the most in its emission, i.e. 106.5 kg in every period. This is because the marginal river damage brought by polluter 5 is the highest among all polluters. When the regulator intends to meet, for example, a 30% reduction in the discounted lake damage over time, polluter 8 contributes the most in a cost-effective solution, i.e. abatement of 169.9 kg in each period. This is because polluter 8 has the largest proportion of its emission contributing to the lake damage. For any set of targets for pollution control, the relative relationship of polluters' marginal contribution is unchanged in an efficient solution to the problem of environmental improvement, which is determined by polluters' environmental damage coefficients in the simulation.

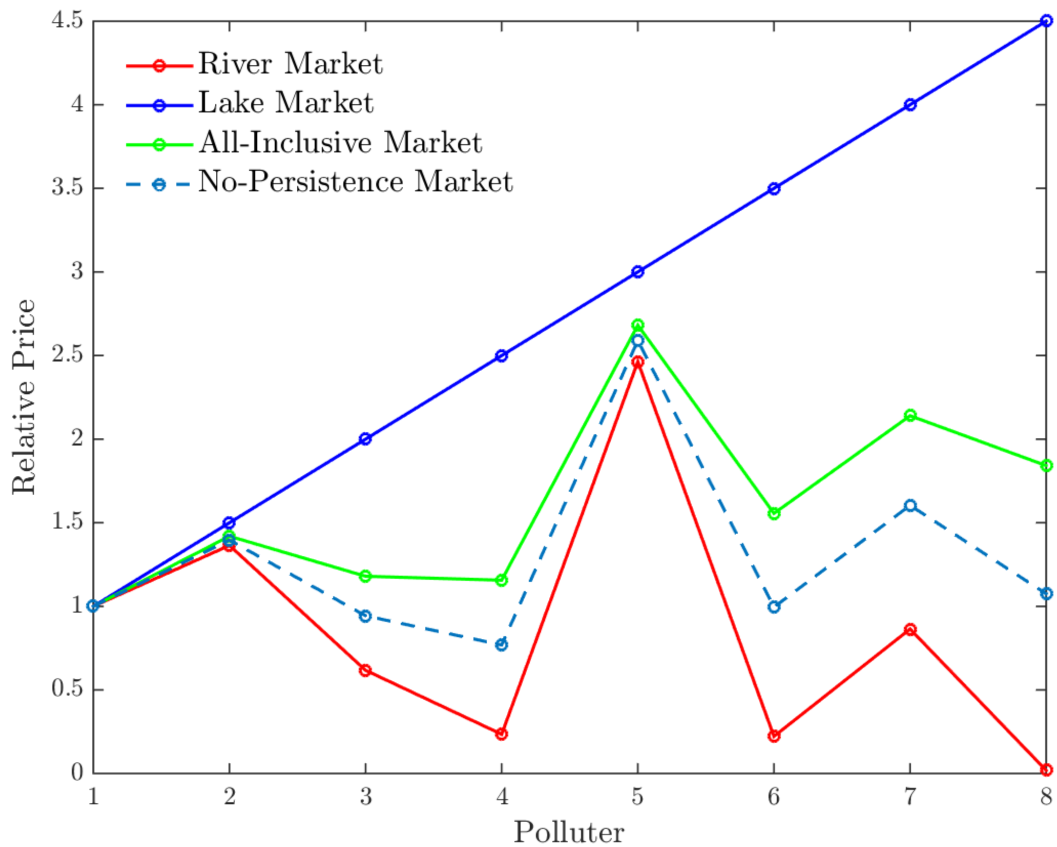


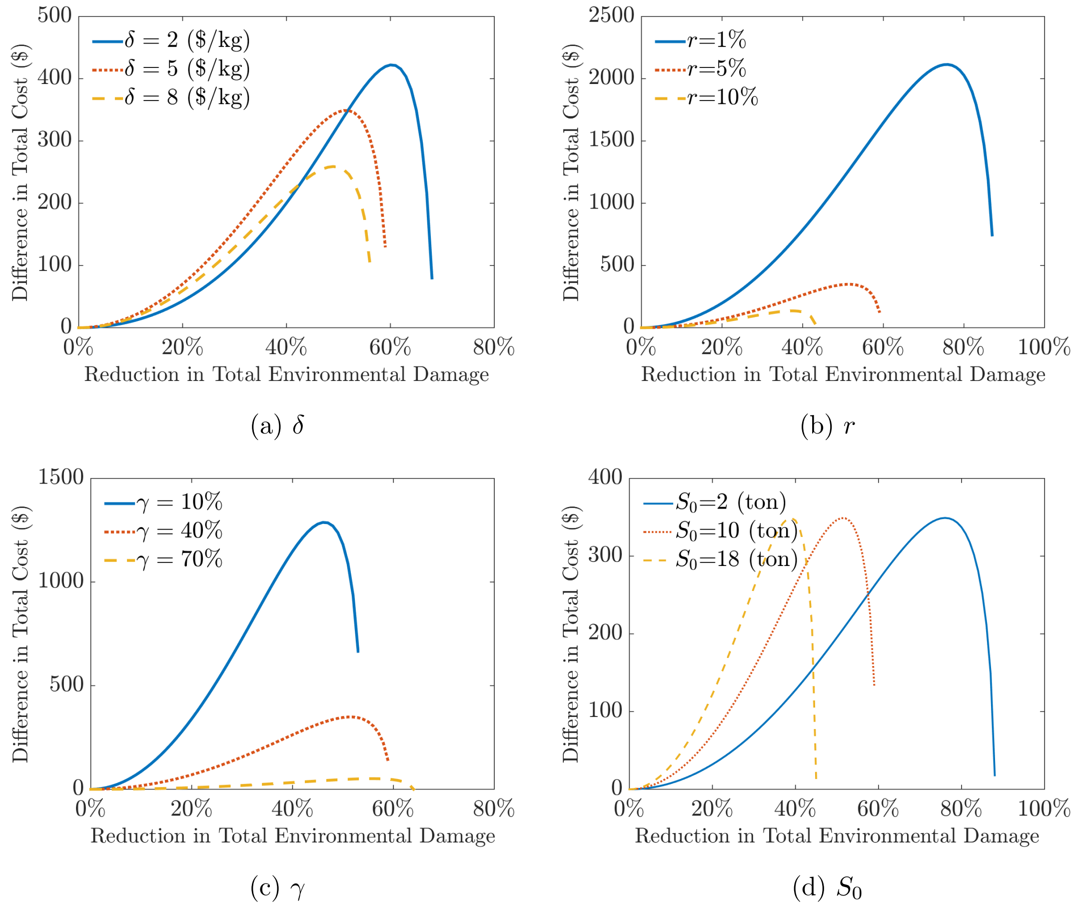
Figure 2.2: Relative Permit Prices of Polluters under Different Scenarios

In the simulation, the permit prices reflect the degree of the importance of each polluter's abatement efforts to alleviate environmental damage. Because the relative relationship of polluters' marginal contribution is constant in an efficient solution, for any set of pollution control targets, the relative permit prices in the corresponding efficient permit trading are constant, too. Figure 2.2 displays these relative permit prices in the market, with the permit price of polluter 1 being normalized to one. In a permit market which derives the cost-effective outcome of pollution control only over river pollution, without considering water quality in the lake (which will be referred to as the river market), the permit prices of polluter 5 and polluter 8 are the highest and the lowest respectively among all polluters. In a permit market which attains the cost-effective outcome of pollution control only over lake pollution, without considering water quality along the river (which will be referred to as the lake market), polluter 1 and polluter 8 have the lowest and the highest permit prices. Based on the prior analysis, all these relative permit prices correspond to their trading ratios, which are related to the ratios of river damage coefficients and the ratios of the transfer coefficients to the lake.

In a permit market which induces the cost-effective outcome of pollution over the discounted total damage (which will be referred to as the all-inclusive market), the relative permit prices appear between those of the river market, as indicated by the red line, and the lake market, as indicated by the blue line. The relative prices in the all-inclusive market take account of polluters' marginal effect on both river pollution and lake pollution.

The dashed line in Figure 2.2 is the relative prices in a permit market, where persistence of lake damage is not accounted for (which will be referred to as no-persistence market). Without considering the continuous environmental damage caused by lake pollution in permit trading, polluters' ability to improve the environment is incorrectly estimated. The corresponding permit prices are distorted and cannot reflect polluters' actual influence on environmental damage. For example, in the all-inclusive market as indicated by the green line in Figure 2.2, the permit prices of polluter 1 and polluter 4 are very close, since these two polluters have similar level of marginal impact on the total damage. However, in the no-persistence market, polluter 4's contribution to reduce the continuous environmental damage of lake pollution has not been accounted for, and its relative permit price turns out lower as a result. Compared with the all-inclusive market, the relative permit prices in the no-persistence market are closer to those of the river market.

In the no-persistence market, the non-uniform mixing problem of water pollution in permit trading is not properly solved. The cost-effective outcome of pollution control is not achieved via this market. The continuous environmental damage of lake pollution is not considered in the no-persistence market, which is influenced by the lake damage coefficient δ, the discount rate r, the decay rate γ, and the initial pollutant stock S_0. Figure 2.3 compares the total abatement cost of the no-persistence market relative to that of the all-inclusive market under these four parameters. We refer this difference in their abatement costs as the cost difference. This cost difference is always positive because the abatement cost of the no-persistence market is at least as high as that of the all-inclusive market. More graphs of the cost difference are available in the appendix.



(a) δ (b) r (c) γ (d) S_0

Figure 2.3: The Cost Difference between No-persistence Market and All-Inclusive Market

The cost difference in Figure 2.3 has an inverse-U shape, and its maximum value is affected by the parameters related to the continuous environmental damage of lake pollution. When a reduction target for pollution control approaches to zero, the cost difference will decrease because polluters' behaviors in the no-persistence market and in the all-inclusive market are akin to those in the unregulated scenario. When a reduction target for pollution control is sufficiently high, the cost difference will also decline since almost everyone approaches complete abatement. This gives an inverse-U shape to the cost difference in Figure 2.3. Moreover, the lake damage coefficient δ, the decay rate γ and the discount rate r can all alter the maximum of the cost difference. For example, the maximum of the cost difference is higher under a lower decay rate. This is because a lower decay rate leads to greater continuous environmental damage caused by lake pollution, and the absence of considering this continuous damage creates a larger distortion in the trading ratios from those in the all-inclusive market. However, the initial pollutant stock S_0 does not change the maximum of the cost difference, in that it does not affect the marginal contribution of polluters in the environment, and does not bring about a greater distortion in the trading ratios from the efficient ones. Although this cost difference in Figure 2.3 is small relative to the total abatement cost, it proves that the non-uniform mixing problem is not solved in permit trading.

Figure 2.3 also indicates that the maximum achievable reduction target for pollution control varies, depending on the parameters related to the continuous environmental damage of lake pollution. The total damage involves the continuous environmental damage caused by polluters in the lake and also the continuous environmental damage generated by the initial pollutant stock S_0 in the lake. Regarding this initial pollutant stock, it can be only removed through the decaying of the pollutant itself. In this sense, the higher the continuous environmental damage caused by S_0 relative to the total damage, the lower the maximum reduction target for pollution control can be attained by polluters.

2.5 Conclusion

This paper points out the necessity of including both flow pollution and stock pollution in solving the non-uniform mixing problem of water pollution. Previous studies on WQT develop trading ratios to account for the diversity in the degree of environmental damage caused by emissions from different locations, but most neglect heterogeneity in persistence of environmental damage. This paper contributes to the previous literature on WQT by involving the difference of environmental damage persistence caused by pollutants from different locations. The cost-effective pollution control outcome can be achieved through permit trading, although complete information on polluters' costs is necessary when there are separate targets at flow pollution and stock pollution. This paper derives the proper trading ratios of permit trading to meet the cost-effective outcome of pollution control, under the linearity assumption on environmental damage. Konishi et al. (2015) point out the difficulty of deriving proper damage-based trading ratios without this linearity assumption in attaining the cost-effective outcome of pollution control. They conclude that in the presence of nonlinear environmental damage, the trading ratios are not necessarily independent of individual emissions, and deriving these ratios also requires complete information on polluters' costs. Nonlinear environmental damage of stock pollution also requires time-dependent trading ratios. Further research is necessary to develop proper trading ratios that can assist to arrive at the cost-effective outcome of pollution control under a less stringent assumption on environmental damage.

Chapter 3

Reliable Reduction in Agricultural Runoff under Environmental Uncertainty

3.1 Introduction

In the 2012 National Water Quality Inventory conducted by the Environmental Protection Agency (EPA), agricultural activity was identified as the top source of impairments in rivers and streams, and the third source of impairments in lakes, reservoirs, and ponds. Excessive nutrients in agriculture runoff are linked to eutrophication, as well as other problems that negatively affect aquatic biomes and degrade ecosystem services. Between 2000 and 2015, about 0.8 million metric tons of nitrogen (nitrate and nitrite) entered the Gulf of Mexico every year, which created a “Dead Zone” covering an area about the size of Connecticut and Rhode Island combined (6,474 square miles) (United States Geological Survey, 2015; National Oceanic and Atmospheric Administration, 2015).

When the environment is uncertain, the effects of abatement efforts are likewise uncertain. The current, common practice for pollution control is setting a deterministic target for the average reduction in pollution over time. To some extent, Segerson supports this practice by suggesting in her seminal paper (Segerson, 1988, p.91) that “if the benefits of abatement are not known, the social planner could simply choose the level of abatement that would on average meet an exogenous target level of ambient pollution." Many following studies either take her suggestion or neglect environmental uncertainty in the analysis of environmental policies, such as voluntary programs (e.g., Segerson and Wu, 2006), command and control (e.g., Rabotyagov et al., 2014), taxes (e.g., Suter et al., 2009), water quality trading (e.g., Collentine and Johnsson, 2012) and payments for ecosystem services (e.g., Carpentier et al., 1998; Khanna et al., 2003).

Although advances in biophysical and hydrological modeling can generate reasonable estimates of the effect of farm management practices on agricultural runoff, the resulting improvement in water quality cannot be known with certainty beforehand. Because an average target does not adequately account for the stochastic nature of pollution control, two issues arise. First, the probability of failure to meet a reduction is not directly regulated. Therefore, meeting an average target can mean the target is met in a few periods but missed in many other periods. Second, an average target does not describe the whole picture of water quality improvement. Water quality improvement can come from an average reduction in pollution over time. It can also come from a reduction in the frequency of extreme runoff events. In particular, there are higher expectations of extreme weather and climate events occurring in the future under climate change, which may increase the likelihood of heavy rainfall. Under such circumstances, limiting the occurrence of heavy runoff may be an important management goal.

The common management practice is to use a margin of safety with a reduction target to address these issues. For example, the margin of safety is introduced as a component of Total Maximum Daily Load (TMDL) to account for "uncertainty in predicting how well pollutant reductions will result in meeting water quality standards" (USEPA, ndb). The margin of safety is developed for reliability of pollution control, limiting the frequency of extreme runoff events.

In this paper, I propose the use of a reliability target in controlling pollution resulting from agricultural runoff, where reliability means achieving a given target with a specified probability regardless of environmental changes. The main contribution of this paper is to introduce and analyze a reliability constraint in a water pollution control model. The corresponding water quality improvement is thereby achieved with a specified level of confidence. Rabotyagov et al. (2016) argue that this type of reliable reduction target in pollutants can be used to improve the resiliency of ecosystem services such as improved water quality. Using this reliability target, the pollution control problem of agricultural runoff becomes an optimization problem with chance constraints, i.e., Chance-Constrained Optimization.[1]

Solving a Chance-Constrained problem of pollution control often requires knowledge of the probability distribution of pollution. Unfortunately, this information is typically not available. The common practice in literature is to assume a specific probability distribution for stochastic agricultural runoff. The chance constraint is then transformed into a deterministic constraint using the probability distribution (e.g., Lichtenberg and Zilberman, 1988; McSweeny and Shortle, 1990; Willis and Whittlesey, 1998; Lacroix et al., 2005). However, solution validation depends on how well the distributional assumption approximates the actual. Roy (1952), on the other hand, develops the Safety-First criterion in portfolio management without a distributional assumption. This criterion is based on Chebyshev's inequality, and can also be used in pollution control to derive a robust solution that protects against the worst case of all the possible probability distributions. Roy's method creates a feasible set that meets the chance constraints for all possible probability distributions and is free from misidentification of the actual probability distribution. The feasible set he generates is, nonetheless, much smaller than that of the original chance-constrained problem, which normally leads to tremendously expensive solutions. For this reason, Roy's method has been criticized as being overly conservative. Despite this weakness, the idea of his method is promising in environmental conservation, particularly when information on the distribution of pollution is insufficient. In this paper, I alleviate the over-conservativeness problem of Roy's method by focusing on the right tail of the probability distribution of pollution, which is more likely to result in disastrous consequences. Also, unlike previous studies I first consider the effect of abatement efforts, their combination, and their spatial allocation on the variance of total pollution when determining a cost-effective solution to a reliable reduction, without assuming any matrix of correlation coefficients among individual emission sources.

[1] The algorithms of Chance-Constrained Optimization might take an unreasonably long time to reach a solution. Bertsimas et al. (2011) point out that a chance-constrained problem may be intractable. This means that although the problem can be solved in theory, the solution algorithms might not be completed in polynomial time.

This paper emphasizes the importance of reliability of pollution control under environmental uncertainty, and contributes to develop a method to achieve a reliability target when a probability distribution of pollution is unknown. The empirical study focuses on the nitrogen runoff problem of the Wolf Creek Watershed in Iowa. Given the current available farm-management practices, reliability of pollution control is costly to achieve. To yield a 41% reduction in total pollution relative to the baseline level with a 70% reliability, a 75% loss in agricultural profit relative to the baseline profit level ($59.8 million) must be undertaken, compared with 1.5% loss in agricultural profit ($1.2 million) to achieve a 41% average target. However, this reliability target attains the 41% pollution reduction in nine out of ten years during 2004-2013, while this average target misses the 41% pollution reduction in five out of ten years during 2004-2013 with much higher unfilling gap. A reliability target is a valuable tool when consistently meeting the target is important. Regarding policy implication, this paper suggests that the requirement on reliability of pollution should be properly reflected by the value of a margin of safety in Total Maximum Daily Loads (TMDL).

The paper is organized as follows: Section 2 models the problem of pollution control over agricultural runoff with a reliability target. Section 3 describes the sample area and data. Section 4 uses simulation analysis to analyze the tradeoff between agricultural runoff and agricultural profits in the sample area. Section 5 illustrates how the margin of safety can be correctly set for a TMDL. Section 6 concludes.

3.2 Reliability of Pollution Control

Consider a group of risk-neutral farmers. They try to maximize their profits while controlling agricultural runoff. Let R be the aggregate runoff from those farmers, and let $\bar{R}$ be a specified reduction target, which is set by an environmental authority. The aggregate runoff R depends on both the farm management decisions $\boldsymbol{X}$ and exogenous uncertainty $\boldsymbol{\epsilon}$ in the environment, reflecting unpredictable weather and streamflow conditions. The total profit of those farmers π also depends on $\boldsymbol{X}$ and $\boldsymbol{\epsilon}$, where the crop prices and the costs of different farm management options are assumed constant over time.

Segerson (1988) specifies a cost-effectiveness problem for the regulator, which maximizes the profit or minimizes the loss subject to a constraint on the expected amount of pollution. She argues that the regulator could simply set a target level of reduction that would be attained on average over time. Her approach has been followed by a number of authors (e.g., Segerson and Wu, 2006; Rabotyagov et al., 2014; Suter et al., 2009; Khanna et al., 2003; Carpentier et al., 1998). Let $\boldsymbol{\chi}$ be the action space of all the farmers, and the farm management decisions $\boldsymbol{X} \in \boldsymbol{\chi}$. According to this specification, there is only a quantitative target that limits the average runoff:[2]

$$\begin{aligned} &\max_{\boldsymbol{X}} \mathbb{E}\left(\pi(\boldsymbol{X};\boldsymbol{\epsilon})\right) \\ \text{s.t.}\ \ &\mathbb{E}\left(R(\boldsymbol{X};\boldsymbol{\epsilon})\right) \leq \bar{R}, \\ &\boldsymbol{X} \in \boldsymbol{\chi}. \end{aligned} \tag{$\mathcal{P}1$}$$

Although this problem setup considers the efforts to achieve the reduction targets on average, it is not concerned with how reliable the efforts are, i.e., the probability of a reduction target being achieved. But, water quality depends specifically upon both a decline in the average pollutant amount and a decline in the occurrence of heavy runoff. If heavy runoff events have disproportionate impacts on water quality, it is important to consider these events in the optimization problem. The importance of extreme events suggests a different target in pollution control, especially when the variance of agricultural runoff is large.

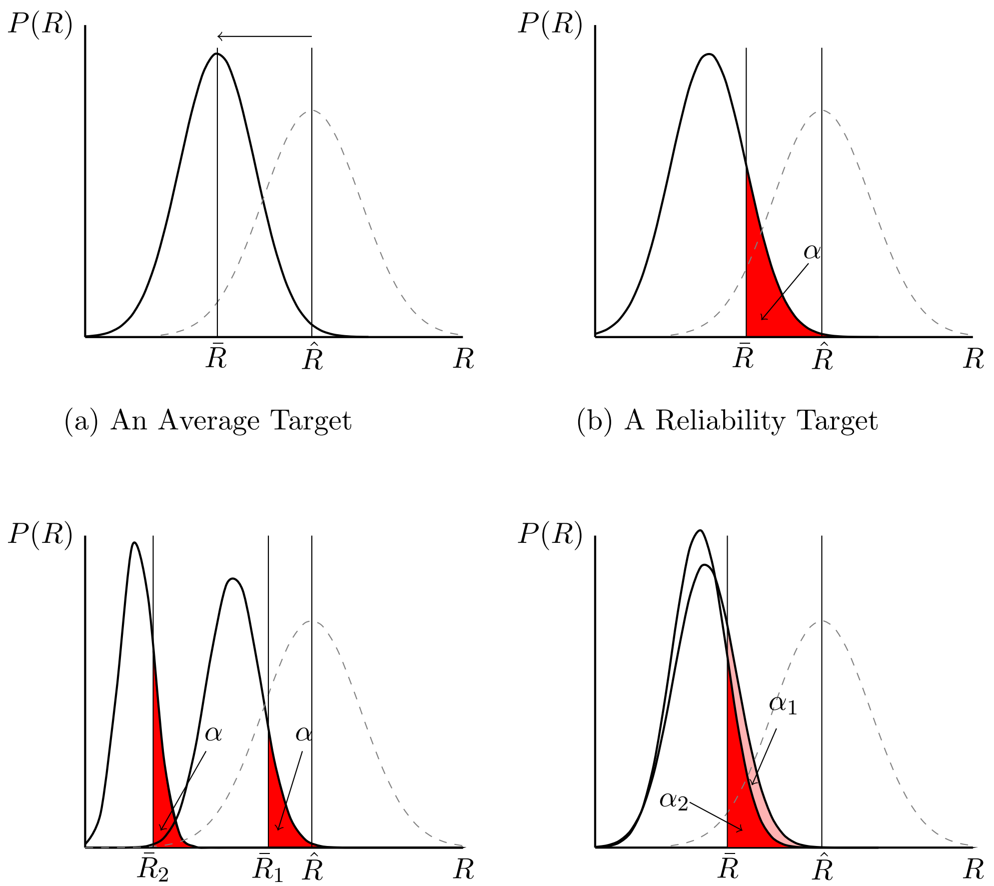
3.2.1 Reliability Target

There are two methods to model farmers' decisions regarding abatement practices under environmental uncertainty. One method is discrete stochastic programming. In this approach, deterministic constraints must be met in both discrete and stochastic scenarios by choosing a specific option in each state. This paper does not use this approach because it is difficult to define discrete scenarios and obtain the corresponding probability of each scenario. Therefore, the second method, Chance-Constrained Programming (CCP), is more appropriate. Let's set an upper bound α on the probability that a

[2] Usually there are more than one type of pollutant that need to be controlled in the runoff. However, the number of pollutant types only changes the number of restrictions in the problem. It does not fundamentally alter the problem setup. For parsimony, I focus on one type of pollutant in this paper.

reduction target is not attained in a period. In other words, a reduction target should be achieved with an assurance level no less than $1 - \alpha$. This probabilistic constraint is called a reliability requirement. A reduction target $\bar{R}$ and a reliability target α together comprise a reliability target. The problem with a reliability target for pollution control is:

$$
\begin{aligned}
&\max_{\boldsymbol{X}} \mathbb{E}\left(\pi(\boldsymbol{X}; \boldsymbol{\epsilon})\right) \\
\text{s.t.} \quad & \mathbb{P}\left(R(\boldsymbol{X}; \boldsymbol{\epsilon}) \geq \bar{R}\right) \leq \alpha, \\
& \boldsymbol{X} \in \boldsymbol{\chi}.
\end{aligned} \tag{$\mathcal{P}2$}
$$



(a) An Average Target

(b) A Reliability Target

(c) Reliability Targets: Reduction

(d) Reliability Targets: Reliability

Figure 3.1: Average Targets and Reliability Targets

Figure 3.1 shows the difference between average targets and reliability targets in pollution control. Typically, a reduction in pollution is accompanied by a reduction in the variance of pollution, while the size of the variance reduction depends on different abatement practices and their spatial allocation. Figure 3.1(a) displays an average target that only limits the average pollutant runoff to $\bar{R}$, regardless of the probability in the right tail. However, a reliability target in Figure 3.1(b) concerns the right tail of the runoff distribution. It restricts the probability of exceeding a reduction target $\bar{R}$ to a reliability requirement α which is represented by the red area. Figure 3.1(c) shows the scenario that requires the same reliability level but more reduction. The probability distribution of pollution moves further to the left, while keeping the same probability of the right tail, i.e., the red area in the figure. Figure 3.1(d) displays the scenario that requires a higher reliability but the same reduction. Previously, the reliability requirement is α_1, which is the sum of the pink area and the red area. The new reliability requirement α_2 is more stringent, and the new runoff distribution moves further to the left. The pink area is not included in the new distribution at reliability level α_2.

3.2.2 Mean and Variance of Agricultural Runoff

Regardless of the complexity of the solution algorithms, CCP is challenging to solve because there is limited information on the actual probability distribution of pollution in the chance constraints. Rabotyagov et al. (2014) use a bootstrap procedure, and Lacroix et al. (2005) use a Monte Carlo simulation based on the probability of the random parameters, all in an attempt to approximate the actual probability distribution of pollution. However, these methods only work well if there are plenty of observations, or if the probability information on the parameters is accurate. In this paper, I solve CCP based on the mean and the variance of agricultural runoff. Although this information is still not sufficient to specify the actual probability distribution, it can be used to obtain a robust solution to the CCP, which will be discussed shortly.

Except for a few cases where aggregate pollutant runoff is assumed to be a function of normally distributed parameters, so that the mean and the variance can be calculated directly from the function (e.g., Bystrom et al., 2000; Vasquez et al., 2000; Melching and Bauwens, 2001; Tze Ling and Eheart, 2005), most studies make an additional assumption on the correlation among individual sources in the computation. The mean and the variance of the aggregate runoff are:

$$\begin{aligned} \mu(\boldsymbol{X};\boldsymbol{\epsilon}) &= \sum_i d_i \mu_i(\boldsymbol{x_i};\boldsymbol{\epsilon}), \\ \sigma^2(\boldsymbol{X};\boldsymbol{\epsilon}) &= \sum_i d_i^2 \sigma_i^2(\boldsymbol{x_i};\boldsymbol{\epsilon}) + \sum_{i \neq j} \rho_{ij} d_i d_j \sigma_i(\boldsymbol{x_i};\boldsymbol{\epsilon}) \sigma_j(\boldsymbol{x_j};\boldsymbol{\epsilon}), \end{aligned}$$

where $\mu_i(\boldsymbol{x_i})$ is the mean of pollutant runoff from source i, $\sigma_i(\boldsymbol{x_i};\boldsymbol{\epsilon})$ is the standard deviation of pollutant runoff from source i, d_i is a delivery coefficient of the pollutant and ρ_{ij} is the correlation coefficient between source i and source j. Some authors assume that runoff from individual sources is independent so that $\rho_{ij} = 0$ for all $i \neq j$ (e.g., Beavis and Walker, 1983), while others impose a series of values on the correlation coefficients (e.g., Lichtenberg and Zilberman, 1988; McSweeny and Shortle, 1990). More recently, some authors have used a biophysical model to compute coefficients (e.g., Rabotyagov, 2010; Rabotyagov et al., 2014).

My approach differs in that I do not make an assumption on the correlation coefficients among individual sources. Instead, the actual influence of abatement practices and their spatial allocation on the mean and the variance of agricultural runoff is included in the computation. Farmers make decisions on their land first, pollutant runoff is summed up to the watershed level, and the mean and the variance are derived afterward:

$$\begin{aligned} \mu(\boldsymbol{X};\boldsymbol{\epsilon}) &= \frac{1}{T} \sum_t \sum_i d_i R_{i,t}(\boldsymbol{x_i};\boldsymbol{\epsilon}), \\ \sigma^2(\boldsymbol{X};\boldsymbol{\epsilon}) &= \frac{1}{T-1} \sum_t \left(\sum_i d_i R_{i,t}(\boldsymbol{x_i};\boldsymbol{\epsilon}) - \mu(\boldsymbol{X};\boldsymbol{\epsilon}) \right)^2, \end{aligned}$$

where $R_{i,t}(\boldsymbol{x_i};\boldsymbol{\epsilon})$ is the individual runoff from source i in year t, and T is the length of the sample time period. While this method increases the computational burden in the optimization step, it avoids a subjective assumption about the correlation among pollutant runoff from individual sources. It also provides a different perspective on computing the variance: instead of figuring out the complex correlation among individual sources, it directly calculates the variance of aggregate pollutant runoff.

3.2.3 Robust Solution

If there is clear information on the probability distribution of agricultural runoff, for example, a normal distribution, a chance constraint in pollution control can be transformed into its equivalent which is a combination of the mean and the standard deviation of agricultural runoff.[3] Let ϕ_α be the critical value of the standard normal distribution such that $\Phi(\phi_\alpha) = 1 - \alpha$. The chance constraint in $\mathcal{P}2$ becomes:

$$\mu\left(\boldsymbol{X};\boldsymbol{\epsilon}\right) + \phi_\alpha \sigma(\boldsymbol{X};\boldsymbol{\epsilon}) \leq \bar{R}. \tag{3.1}$$

Compared with an average target, the reliability target adds a penalty ϕ_α on the standard deviation of pollution. The cost-effective farm management decisions are hence determined by a balance among the marginal change in the expected profit, the marginal change in the mean of pollution, and the marginal change in the variance of pollution. Due to the uncertain relation between farm management and the variance of pollution reduction, the marginal benefit or the marginal abatement cost in the cost-effective solution could be higher or lower than without a reliability requirement.

Following the analysis above, a reliability target is not just making a more stringent target for pollution control. Actually, an effort to meet a reliability target can be decomposed into two aspects. On one hand, this effort is undertaken to implement more conservative practices so as to meet a more stringent target (when a reliability level is high). On the other hand, this effort is made to change the spatial distribution of abatement practices in order to reduce the variance of total pollution. Regarding specific abatement practices, unlike the scenario of meeting an average target, their effect on both the expectation and the variance of pollution are considered in achieving a reliability target. For example, two abatement practices generate the same expected abatement cost. The one which reduces more pollution on average will be preferred to meet an average target. However, it is not necessarily true for a reliability target, because the practice which causes a slightly higher average pollution but a much lower variance of pollution may be preferred to meet a reliability target.

However, whether or not the solution above is valid depends on how close the actual distribution of pollution is to a normal distribution. Figure 3.2 displays three possible

[3] Kampas and White (2003) think that the choice of a distributional assumption usually depends on data availability and the concerns of the regulator or decision-makers. However, a normal distribution is commonly chosen in previous studies for the reason of convenience.

probability density functions, given the same farm management choices. These distributions have the same mean and the same variance. The gray dashed curve is a normal distribution. If the actual runoff is close to this distribution, the solution above meets the reliability target: the probability of achieving a reduction target $\bar{R}$ is greater than $1 - \alpha$. However, the actual runoff does not necessarily follow a normal distribution. It might be the red curve, which meets the reliability requirement. It might also be the blue curve, which fails to attain the reliability target.

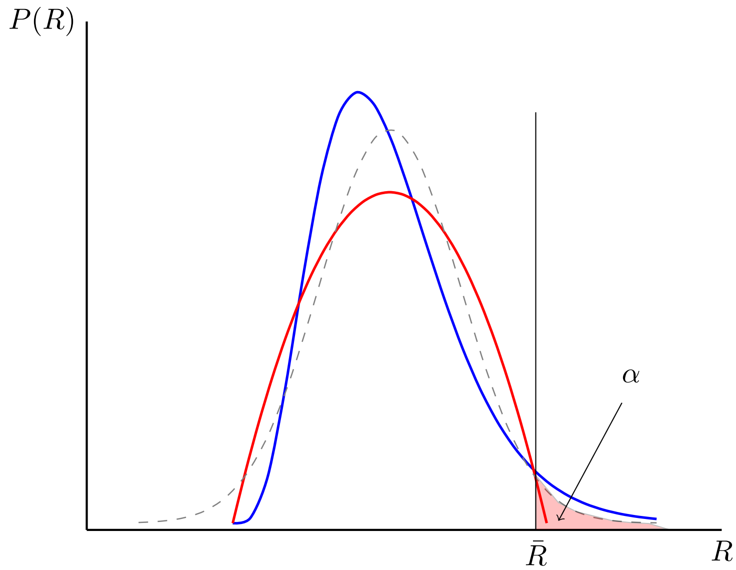


Figure 3.2: Different Probability Distributions of Pollution

Without clear information on the probability distribution, Roy (1952) develops a safety-first criterion to derive a robust solution to CCP. This criterion constructs a feasible set to protect against the worst case of all possible distributions in the problem, which is typically much smaller than the one of the original CCP. Therefore, Roy's method guarantees that no matter the distribution of agricultural runoff, the farm management choices in the solution always meet the reliability target. Roy's method is based on the most common version of Chebyshev's inequality:

$$\mathbb{P}\left(\frac{|R(\boldsymbol{X};\boldsymbol{\epsilon}) - \mu(\boldsymbol{X};\boldsymbol{\epsilon})|}{\sigma(\boldsymbol{X};\boldsymbol{\epsilon})} \geq \delta\right) \leq \frac{1}{\delta^2}, \tag{3.2}$$

where $\delta \in \mathbb{R}^+$. This inequality concerns the deviation of $R(\boldsymbol{X};\boldsymbol{\epsilon})$ from $\mu(\boldsymbol{X};\boldsymbol{\epsilon})$ in both directions and provides a maximum probability that $R(\boldsymbol{X};\boldsymbol{\epsilon})$ falls out of a given range. Using this inequality, the chance constraints in CCP are transformed into deterministic constraints, which are the sufficient but not necessary conditions of the chance constraints. The problem with this method is that it is overly conservative. However, the idea of constructing a feasible set to protect against the worst case of the possible probability distributions in the problem is promising and reasonable in environmental protection.

The present paper follows Roy's idea and improves his method by using a robust but less stringent transformation of the chance constraints. A regulator will only care about one tail of the distribution: the probability of pollutant runoff being too large. Because of this, there are two other inequalities that are preferred to use than the most common version of Chebyshev's inequality. One is Cantelli's inequality, which is also called the one-sided Chebyshev's inequality:

$$\mathbb{P}\left(\frac{R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})}{\sigma(\boldsymbol{X};\boldsymbol{\epsilon})} \geq \delta\right) \leq \frac{1}{1+\delta^2}. \tag{3.3}$$

The other is a semivariance inequality which is derived by Berck and Hihn (1982). This semivariance is smaller than the variance because it only focuses on the deviation when pollutant runoff is higher than the average:

$$\begin{aligned} &\mathbb{P}\left(\frac{R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})}{\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})} \geq \delta\right) \leq \frac{1}{\delta^2}, \\ &\text{where } \hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon}) = \sqrt{\int_{\mu(\boldsymbol{X};\boldsymbol{\epsilon})}^{+\infty} \left(R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})\right)^2 \mathrm{d}F(R)}. \end{aligned} \tag{3.4}$$

The proofs of Cantelli's inequality and the semivariance inequality are available in the appendix. These two inequalities focus only on the probability of heavy runoff and apply to all possible distributions as long as their mean and variance exist.

Using inequality (3.3), the corresponding sufficient but not necessary condition of the chance constraint is,

$$\mu(\boldsymbol{X};\boldsymbol{\epsilon}) + \sqrt{\frac{1}{\alpha}-1}\ \sigma(\boldsymbol{X};\boldsymbol{\epsilon}) \leq \bar{R}.$$

Using inequality (3.4), the corresponding sufficient but not necessary condition of the chance constraint is,

$$\mu(\boldsymbol{X};\boldsymbol{\epsilon}) + \sqrt{\frac{1}{\alpha}}\ \hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon}) \leq \bar{R}.$$

Combining the two inequalities, a robust transformation of the chance constraint is:

$$\min\left(\mu(\boldsymbol{X};\boldsymbol{\epsilon}) + \sqrt{\frac{1}{\alpha} - 1}\ \sigma(\boldsymbol{X};\boldsymbol{\epsilon}),\quad \mu(\boldsymbol{X};\boldsymbol{\epsilon}) + \sqrt{\frac{1}{\alpha}}\ \hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})\right) \leq \bar{R}. \tag{3.5}$$

The first formula tends to be the bound when total pollution has a smaller deviation from both directions of greater than and smaller than the average. The second formula tends to be bounded when total pollution has a smaller deviation from the direction of greater than the average. In the following empirical study, the first formula is likely to be the bound when a reliability level is not high, while the second formula is likely to be bounded when a reliability level is high.

3.3 Empirical Application

The 2008 Gulf Hypoxia Action Plan sets a 45% target reduction in riverine nitrogen load and riverine phosphorus load to control hypoxia in the Gulf of Mexico and to improve overall water quality (Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008). It asks for states along the Mississippi River to develop statewide nutrient reduction strategies. Responding to the Action, the Iowa Department of Agriculture and Land Stewardship and Iowa State University cooperated to assess the nutrient loading from Iowa to the Mississippi River and also to study best management practices (BMPs) for agriculture (Iowa State University Science Team, 2013). The study finds that nonpoint sources should reduce nitrogen by 41% and phosphorus by 29% to achieve a 45% total load reduction. Moreover, nine priority 8-digit Hydrological Unit Code (HUC) watersheds were identified as part of the Iowa Nutrient Reduction Strategy.[4]

These watersheds were chosen according to "[nitrogen and phosphorus] loads and concentrations, presence of point sources, landform distribution throughout the state, and engagement of active, local groups within these watersheds" (Water Resources Coordinating Council, 2014). The study area in the paper is the Wolf Creek Watershed,

[4] An HUC consists of two to twelve digits. The more digits it has, the finer area it identifies. For example, 2-digit HUC identifies at regional level, and 8-digit HUC identifies at subbasin level.

displayed in Figure 3.3. It is located in the Middle Cedar River basin, one of the nine priority watersheds. The entire watershed is in No. 104 Major Land Resource Area, which is defined by a specific pattern of soil, climate, water resources and land use (Natural Resources Conservation Service, nd).

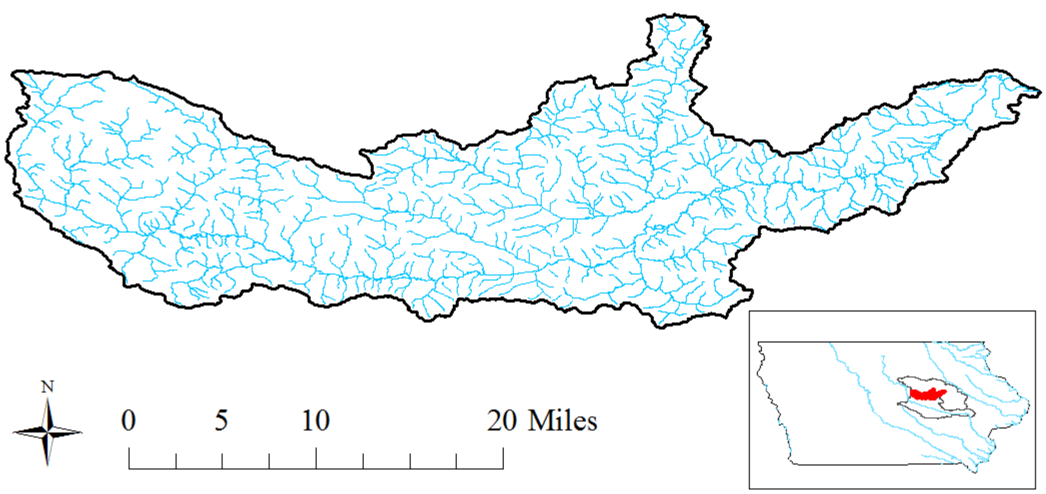


Figure 3.3: The Wolf Creek Watershed in Iowa

The Wolf Creek Watershed includes 846 km^2, i.e. 326.6 square miles. Using the 2008 Crop Data Layer as the baseline land cover, cropland is 83% of the overall watershed. I focus on controlling nitrogen in agricultural runoff in the study area, not only because agriculture is the major contributor of nitrogen, but also because many nitrogen compounds are soluble in water, which means they spread into a broader area and cause health concerns (Powlson et al., 2008; Brender et al., 2013) . In the baseline scenario where farmers do not take any abatement efforts, the aggregate annual crop profit in the watershed is \$79.6 million.

3.3.1 Soil and Water Assessment Tool

The study uses the Soil and Water Assessment Tool (SWAT) to simulate the impact of farm management on crop production and agricultural runoff. The tool is actively supported by the United States Department of Agriculture. After being developed for more than 30 years, this tool has proven to be an effective watershed-based hydrological model for assessing water quality problems (Gassman et al., 2007). The inputs of SWAT include watershed dimensions, climate, hydrologic cycle, sediments, nutrients, pesticide, bacteria, water quality, plant, and farm management (Arnold et al., 2013). In simulations, SWAT segregates a watershed into numerous hydrological response units (HRUs), and estimates water and chemical movement at the HRU level. Within an HRU, land use and soil conditions are homogenous. Dalzell et al. (2012) provide more details of using SWAT in studying water pollution control.

3.3.2 Best Management Practices

Table 3.1: Abbreviations for Farm Management Alternatives

Abbreviation	**Farm Management**
Ba	Baseline
Ac	All crop
Ct	Conservation tillage
Nt	No tillage
Gw	Grassed waterways
Rf	Reduced fertilizer
Cc	Cover crop
Pr	Prairie
Fd	Forest
RN	Reduced fertilizer and No tillage
RC	Reduced fertilizer and Cover crop
NC	No tillage and Cover crop
RNC	Reduced fertilizer, No tillage, and Cover crop

The SWAT model in this paper contains 13 farm management alternatives, including the baseline scenario where farmers make no abatement efforts. These alternatives involve three categories of BMPs: One is land retirement, the conversion of cropland into prairie or forest; another is structured practices, such as tillage and cover crop, which changes the configuration of landscape and is easily observable; the third is non-structured practices such as reduced application rate of fertilizer, which is not observable.

Table 4.2 lists the abbreviations for all farm management alternatives. The description of each alternative is available in the appendix. Among the available farm management options, planting cover crops seems promising to control nutrient runoff. However, there is currently no agreement on how cover crops impact crop yields. The Iowa Nutrient Reduction Strategy reports an average 6% reduction in corn yield following a rye cover crop. By contrast, the Conservation Technology Information Center (2015) reports a 2.1% increase in corn yield and a 4.2% increase in soybean yield following cover crops. Learning Farms and Practical Farmers of Iowa (2015) provides a possible explanation of such divergence: the difference in crop yields is due to whether or not a cover crop is properly managed. For example, if a rye cover crop fails to be terminated completely by herbicide, it is likely to compete with crops in the early growing season, and therefore negatively affect crop growth. If a cover crop is appropriately managed, it is most likely to have little or no negative effect on crop yield. In this paper, I assume no yield benefit or yield loss associated with a cover crop.

3.3.3 Crop Enterprises

Cropland in the Wolf Creek Watershed is all in corn-soybean rotation. In order to eliminate the effect of different orders of corn-soybean rotation on a change of crop production and nitrogen runoff, I assume that half of the cropland grows corn and the other half grows soybean each year. Farm management costs involve seeds, chemicals, machinery, labor and other miscellaneous expenses. Land rent is not included. The cost of chemicals, labor and machinery are adjusted properly to reflect different farm management practices, based on studies of conservation practices in Iowa (Kling et al., 2007; Iowa State University Extension, 2013; Duffy and Calvert, 2015) and the Iowa Nutrient Reduction Strategy. Table 3.2 reports the costs of farm management alternatives in 2015 USD. Details are available in the appendix. Additionally, by assuming constant input and output prices over time, I eliminate the effect of price volatility on farm management decisions. Changes in farm management decisions come from a balance between crop production and nitrogen runoff. The market price of corn is

\$218.91/metric ton, and the price of soybean is \$477.68/metric ton.[5] These are Iowa inflation-adjusted averages for 2011-2015. Moreover, although forest, timber, and grass can bring about economic values, such values are not counted here because there is currently no established market for them and price information is not available. In this regard, the cost estimates for land retirement would be higher than its actual cost.

Table 3.2: Estimated Crop Production Cost in Corn-Soybean Rotation (\$/acre)

Management	**Corn**	**Soybean**	**Management**	**Corn**	**Soybean**
Ba	484.33	287.96	Nt	476.66	301.80
Ac	484.33	287.96	RN	463.62	290.83
Rf	471.29	283.16	NC	544.61	367.99
Gw	577.08	381.32	RNC	531.57	363.08
Ct	491.82	298.17	Fd*	295.01	295.01
Cc	552.28	362.99	Pr*	171.00	171.00
RC	539.24	356.50			

Note: The costs of forest and prairie costs involve their site preparation, establishment and management.

3.3.4 Total Nitrogen

Total nitrogen (TN) in the study area includes five components of TN: organic nitrogen, NO_3-N in surface flow, NO_3-N in lateral flow, NO_3-N in tile flow and NO_3-N in groundwater, displayed in Figure 3.4. The flow of TN is determined by farm management, weather, and soil conditions. During 2004 to 2013, the annual TN flow in the Wolf Creek Watershed was 2.3 million kilograms on average, but it ranged from 0.6 million kilograms to 4.6 million kilograms. Nitrogen in tile flow is an important part of TN, which receives more attention in the Midwest where tile drainage is extensively applied. Drainage tiles short-circuit many natural processes through trees, shrubs, and grasses in the environment, which would slow down water flows and absorb nitrogen. Nitrogen,

[5] Since the prices are reported in bushels, Hohanns and Smith (2013) suggest converting them into prices per metric ton using conversion rates of 39.37 for corn and 36.74 for soybean.

therefore, moves faster in the tiles to waterways. Nitrogen in the groundwater is influenced by farm management and could cause health concerns directly. Keeler (2013) finds that the conversion of grassland to agriculture in southeastern Minnesota from 2007 to 2012 could increase the number of contaminated wells, i.e., the wells exceeding 10 ppm nitrate-nitrogen, by 45%. However, since there is no observation available in the study area to validate the results, I use the SWAT results on groundwater nitrogen in this paper.

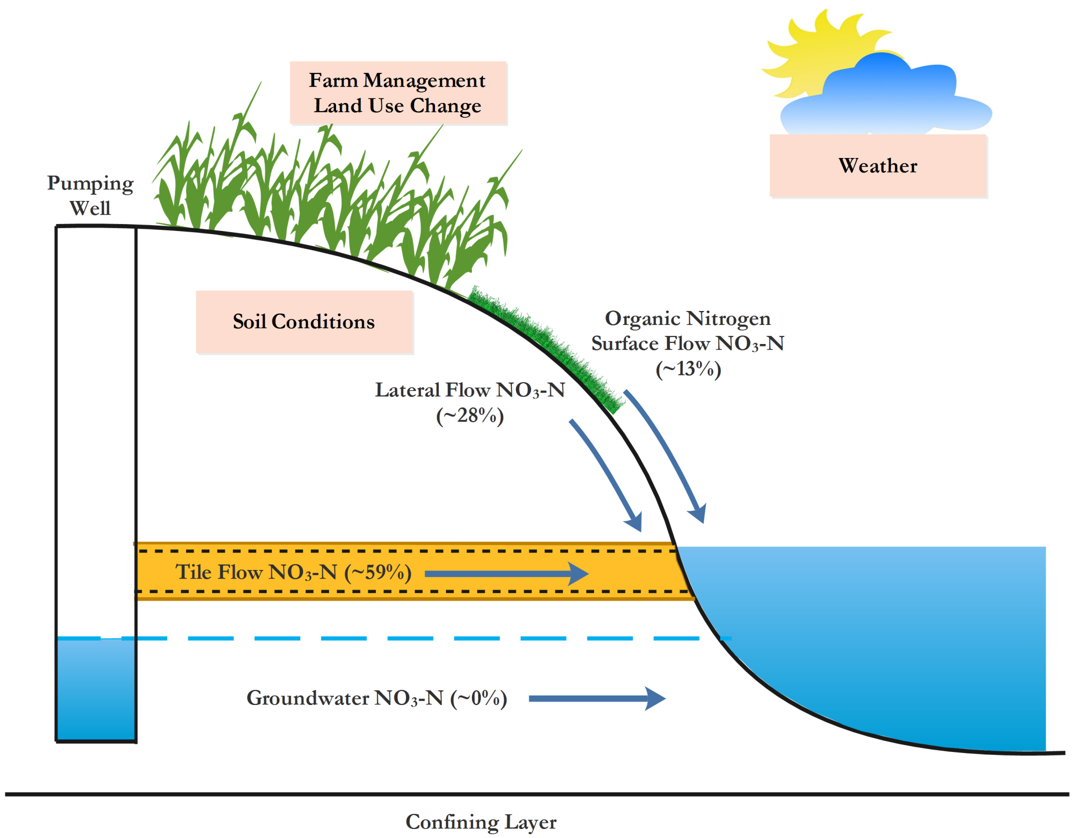
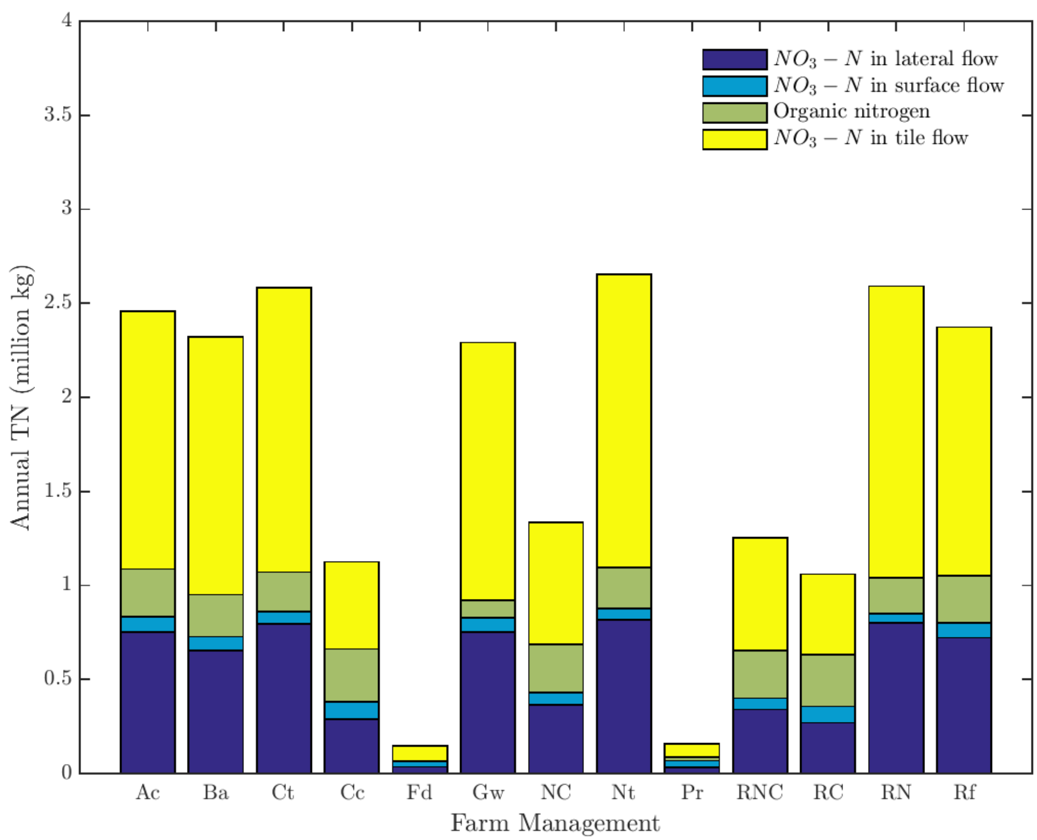


Figure 3.4: Components of Total Nitrogen Runoff in the Wolf Creek Watershed



Note: NO_3-N in groundwater is negligible in total nitrogen, so it is not included here.

Figure 3.5: Total Nitrogen under Different Farm Management in the Wolf Creek Watershed

Farm management influences TN by changing crop growth, nutrient use efficiency, the nitrogen cycle and nitrogen mineralization. Figure 3.5 compares the average TN from 2004 to 2013 in the Wolf Creek Watershed under different farm management practices. These averages are the levels of TN that would have flowed into the watershed annually when one farm management practice was applied to the entire area (except the land used for transportation). Among these farm management alternatives, land retirement performs best in reducing TN, as it removes all agricultural activities on the land.[6] Cover crop also significantly reduces TN, especially NO_3-N in tile flow. Cover crops form a protective canopy to diminish the effect of precipitation on the soil surface, and store underutilized fertilizer before the next rotation of crop is planted. Grassed waterways assist in reducing soil erosion and trapping sediment. This practice effectively reduces organic nitrogen but has little influence on other nitrogen components. Conservation tillage and no tillage, if not properly allocated, might generate higher nitrogen runoff than the baseline.

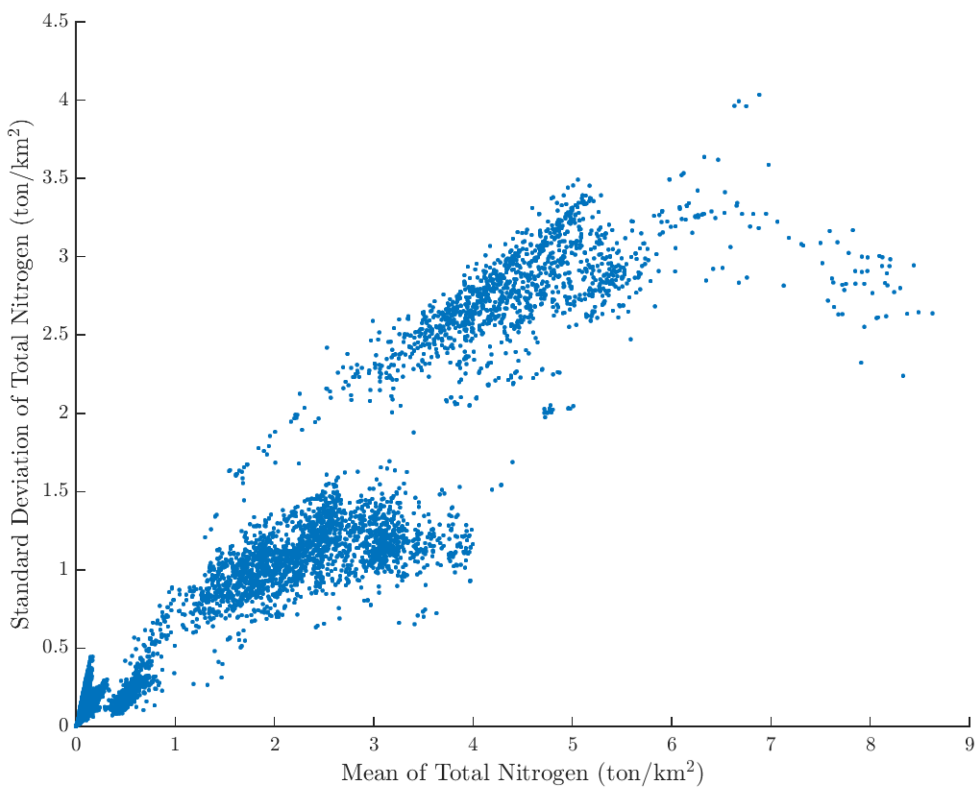


Figure 3.6: Mean and Standard Deviation of Total Nitrogen at HRU Level

Figure 3.6 shows the relationship between the average and the standard deviation

[6] During SWAT simulation, tile drainage is not removed when land is converted to prairie or forest. That is the reason why NO_3-N in tile flow still exists. While this affects the amount of different components of TN, it makes little change to the overall value of TN.

of TN, over the ten-year study period, at the HRU level under the baseline scenario. On the one hand, when TN is not large, there is a positive correlation between the average and the standard deviation of TN. In other words, the smaller the runoff, the smaller the range over which it fluctuates. TN variance is roughly inversely related to average abatement. On the other hand, when TN is very large, its variance seems to decrease slightly. Moreover, there is a wide range of standard deviations of TN for any given level of TN. Decisions on pollution control are not as simple as determining the level of average reduction. These decisions should take into account a level of standard deviation of TN, which will be even more complex if one includes the spatial correlation between different HRUs. In this regard, it is essential to consider carefully the spatial characteristics, the reduction effect and reliability of an induced reduction for different farm management alternatives, to generate a reliable reduction in TN.

3.4 Results

Processing the simulation data on the effect of farm-management practices on crop production and agricultural runoff, and solving the optimization problem of pollution control using MATLAB with Cplex solver, we can derive the solutions to different targets on agricultural runoff.[7] More details of the optimization models are available in the appendix. In order to achieve a 41% reduction in agricultural nitrogen runoff, as specified in the Iowa Nutrient Reduction Strategy, a $1.2 million loss in crop profit is incurred annually if using only an average target. The marginal cost of abatement is $15.6/kg. An opportunity for a win-win exists: i.e., to decrease TN without bringing down the crop profit below the baseline, as long as agricultural expansion is allowed and a reduction target is below 38%.[8] Nevertheless, if using a reliability target with 70% reliability level to meet a 41% reduction, there will be a $59.8 million loss in crop profit annually in a robust solution, i.e. 75% of the baseline profit. Compared with Roy's

[7] This paper uses a MATLAB toolbox called XProg to transform the optimization problem here into a mixed-integer programming that can be solved via Cplex. The MATLAB toolbox is publicly available on the website http://xprog.weebly.com/.

[8] Farmers are not applying their optimal farm-management practices in the baseline scenario based on the spatial data and farmer surveys available. However, this result might change if there is more precise data on farm management of each farm in the watershed is available, because we base our computation on farmer surveys which reflect the general conditions on farm management which do not consider the heterogeneity among each farm.

method, the improved robust solution in the paper alleviates the over-conservativeness problem by increasing \$1.1 million in the annual agricultural profit. The marginal cost of abatement is \$46.7/kg. If there is more information on the probability distribution of pollution, it is likely to be less loss in crop profit. For example, if TN follows a normal distribution, the loss in annual crop profit is \$27.2 million, i.e., 34% of the baseline profit, to meet the 70% reliability requirement.

3.4.1 Agricultural Profit and Spatial Allocation

Figure 3.7 displays agricultural profits under different reliability targets. In general, it is more difficult to initiate a reduction at a higher reliability level. The shape of each agricultural profit curve is roughly concave with respect to a TN reduction level, implying an increasing marginal cost of abatement. Agricultural profit also declines as the reliability requirement increases. Agricultural profit curves under different reduction targets converge when a reliability level is either very high or very low. Additionally, due to a complicated relationship between TN variance and abatement efforts, enhancing the reliability level by 1% does not necessarily lead to an increase in the corresponding marginal cost of abatement. Therefore, the shape of agricultural profit under different reduction targets is not necessarily concave. For example, under a TN reduction target of 20%, the marginal cost to achieve an additional unit of reliability is \$0.69 million at a 50% reliability level, and \$0.60 million at a 60% reliability.

Figure 3.8 displays the proportions of the areas of cost-effective abatement efforts under different reduction targets. Cover crops and reduced application rate of fertilizer are important in reducing TN, no matter whether a reliability requirement is imposed or not. Particularly if a reduction target is around 60%, these farm management alternatives are dominant in a cost-effective solution, as they effectively reduce TN while maintaining agricultural production. Under a reliability target with 70% reliability requirement, this group of farm management practices is applied intensively in a robust solution if a reduction target is not high. In addition, land retirement is effective to reliably reduce TN. However, land retirement is very costly not only because it takes time and resources to establish a forest or prairie, but also because it removes all agricultural activities from land. Therefore, Figure 3.8 shows that under an average target, land retirement is considered only when the reduction goal is very high. While land retirement is costly, it is indispensable in achieving a reliable reduction. Moreover, besides cover crops and land retirement, grassed waterways are also important to reduce TN. This practice is used extensively in a reliable reduction, as it is more effective in reducing organic nitrogen than most of the other abatement practices.

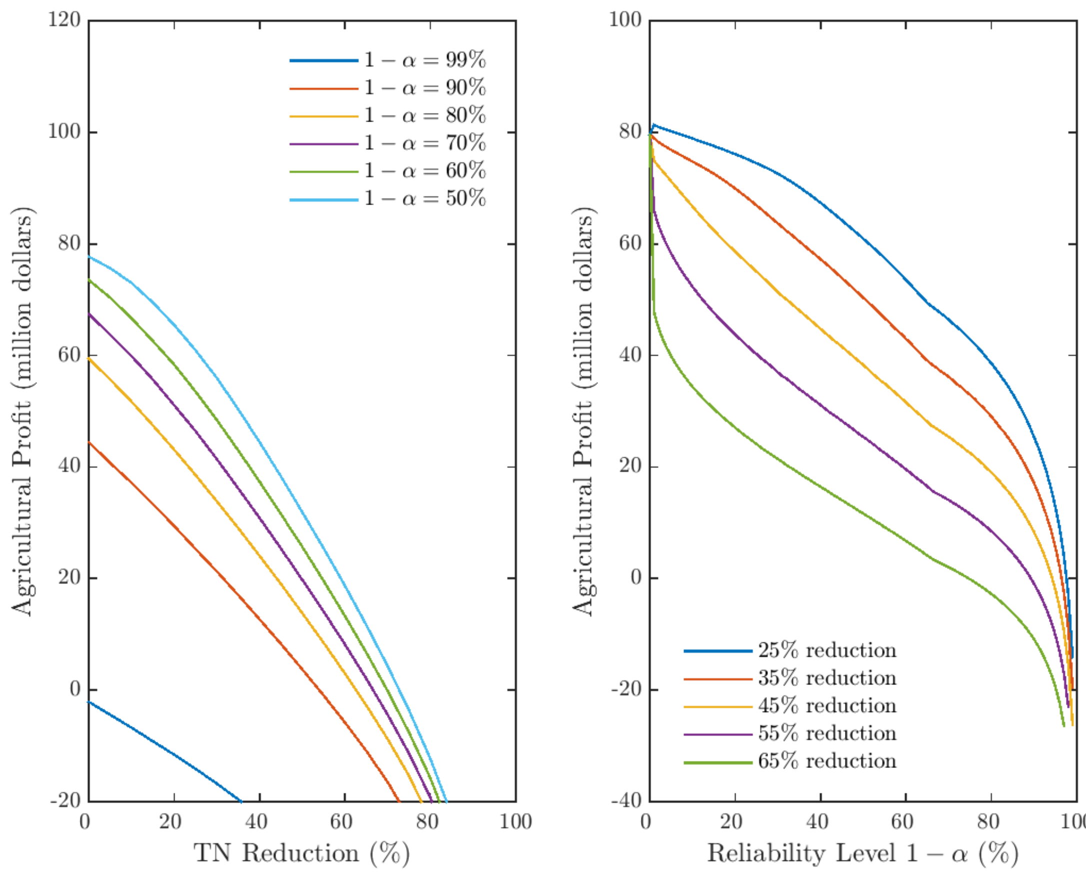
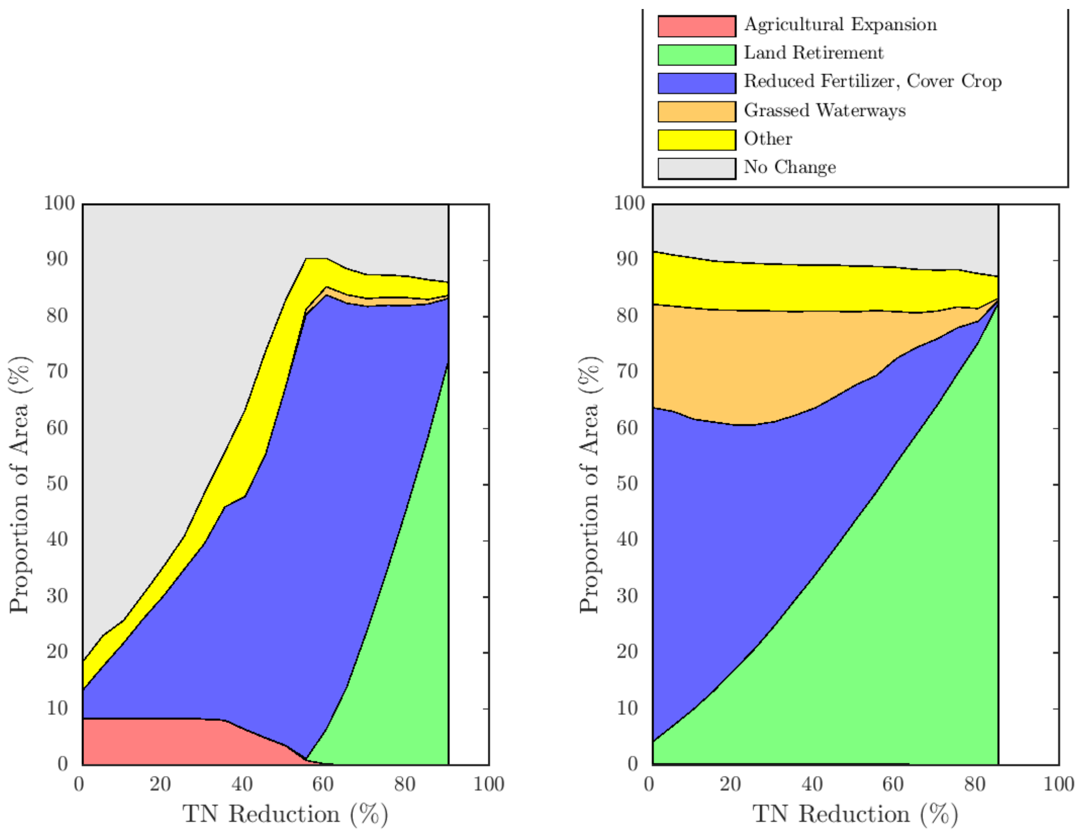


Figure 3.7: Robust Solutions to Total Nitrogen Reduction in the Wolf Creek Watershed

Figure 3.9 compares the spatial allocation of the cost-effective solutions under different reduction targets. At the optimal solution, much of the upper-west and the upper-east areas of the watershed remain in their baseline practices. An opportunity for agricultural expansion in this area under a low average target exists. Reduced application rate of fertilizer and cover crops are preferred in the south of the watershed. When the reduction target is higher, on the right of the figure, this group of farm management alternatives takes a larger area in the south, where grassed waterways were previously applied. Under a reliability target, land retirement is preferred in the west of the watershed, and it starts to take a larger area in the south, where the group of reduced fertilizer and cover crops was applied.



(a) Average Targets

(b) Reliability Targets,70% Robust

Figure 3.8: Farm Management Area under Different Reduction Targets

Furthermore, Figure 3.10 shows that farmers are not equally affected in nitrogen abatement: Some suffer a great loss in agricultural profit, while some may even experience a profit gain. For example, farmers in the upper-west of the watershed and along the Wolf Creek River are less affected than those in the central and the southern areas of the watershed. Particularly, some farmers alongside the Wolf Creek River always have profit gains in a TN reduction. For this reason, policies such as cost-share programs, subsidies, education and extension efforts should take into account the distinctive reduction outcomes of nitrogen runoff on different areas and farmers.

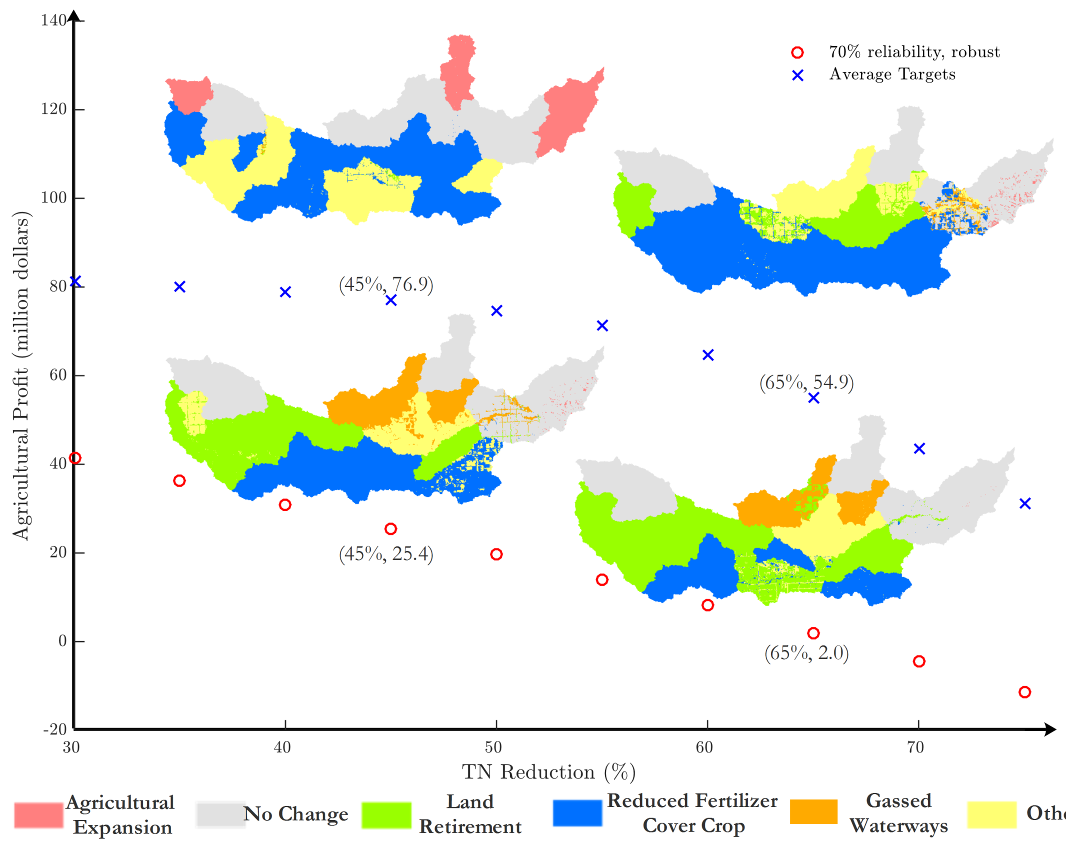


Figure 3.9: Agricultural Profit and Cost-Effective Farm Management

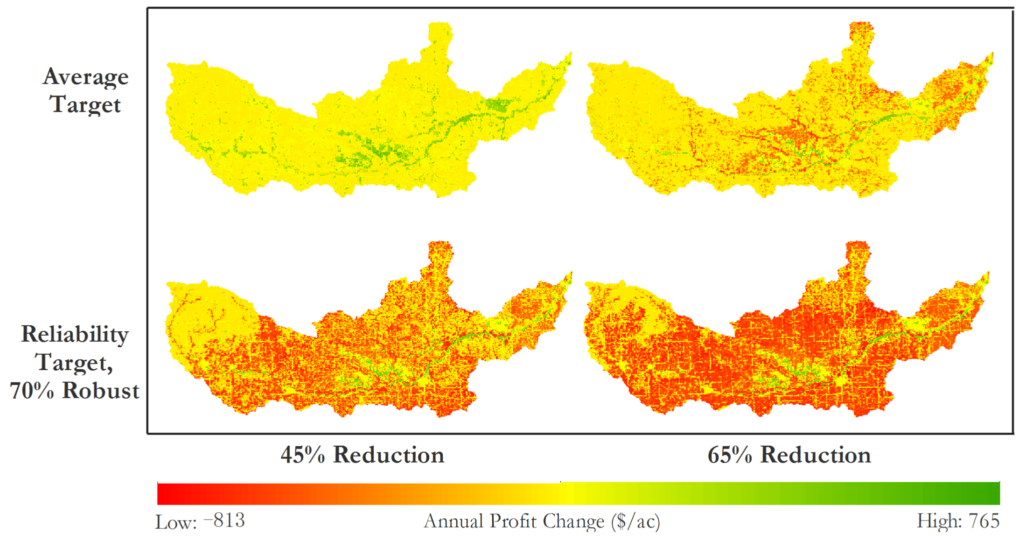


Figure 3.10: Changes in Agricultural Profit under Different Reduction Targets

The estimates on abatement cost in this paper, i.e. the difference between the baseline and the cost-effective agricultural profits, are in general compatible with previous estimates and are within a reasonable range. For example, Doering et al. (1999) estimate the range of average abatement cost of nitrogen from non-atmospheric sources, which is from \$48.12/kg to \$233.33/kg around Albemarle/Pamlico and Chesapeake Bay. Ribaudo et al. (2001) provide a lower average cost varying from \$0.50/kg to \$4.62/kg in the Mississippi Basin. They include a change in social welfare and environmental benefit in the cost. The difference between my estimates and the previous estimates is possibly due to three factors. One is the availability of BMPs. This paper includes several BMPs, such as cover crops and grassed waterways, which are not considered in the previous estimates. With broader availability of BMPs, it is reasonable that the abatement cost here is lower than the previous estimates (as an example, \$11.8 million to achieve the 0.2 million kilograms nutrient reduction, in Harding, 1993). Second is the elements included in abatement cost. The estimation in this paper focuses on the loss in agricultural profit and does not involve administrative costs (e.g., Harding, 1993), or governmental cost and environmental benefits (e.g., Ribaudo et al., 2001). Third is spatial heterogeneity. Agricultural cost and revenue are influenced by local climate, soil, and plant as well as other local factors. While the estimate of abatement cost in, the Tar-Pamlico Basin in North Carolina or the Chesapeake Bay, for example, provides a reference, it cannot be taken as the cost in other places. Indeed, the Wolf Creek Watershed is located in the Midwest of the United States, where cropland is mostly tile-drained. Because the average abatement cost on tile-drained land is substantially lower than that on non-drained land (Petrolia and Gowda, 2006), it is reasonable that the estimates are different from values based on places without tile drainage.

3.4.2 Agricultural Profit and Different Restrictions

It is generally accepted that agricultural profit is reduced more with a smaller array of farm management alternatives. However, there is a concern of local communities, agencies or governments about using some practices for the sake of, for example, protecting the local environment, developing the local economy, or reducing administrative costs. Therefore, some farm management alternatives might not be available in some cases. Table 3.3 compares agricultural profits under five scenarios, according to the availability of farm management alternatives. Under Scenario A all farm management alternatives are available. It has the highest agricultural profit of all the scenarios. Under Scenario B, agricultural expansion is not allowed. The public might worry that if non-cropland is converted for agricultural use, the local biome will be disturbed and the ecosystem services provided by wetlands or forests will be significantly reduced, which is harmful to the local environment. To this end, agricultural expansion is not allowed, thus eliminating possible opportunities for profit increase. Under Scenario C there are no unstructured practices. Unlike a structured practice, an unstructured practice like reduced application rate of fertilizer does not visibly change the configuration of the soil surface. There is no cost-effective way to monitor such practice, however. In order to avoid high monitoring cost and potential misrepresentation, Table 3.3 displays the cost when a reduced application rate of fertilizer and its combinations are not available. Compared with Scenario A, agricultural profit does not decrease much in Scenario B and C. Scenario D does not allow cover crops. As a traditional management option in agriculture, a cover crop is not used to produce harvestable crop but to fertilize and protect the soil. Very recently, it has begun to attract attention as a way to control agricultural runoff. From Table 3.3, cover crops are apparently important in TN reduction. Agricultural profit drops significantly when a cover crop is not available, because cover crops are widely applied in a cost-effective solution to control nitrogen runoff. Under Scenario E, land retirement is not available. Land retirement is very effective and also indispensable in achieving a high reduction, as well as a reliable reduction. Without land retirement, it is impossible to meet a reliability requirement or to achieve a reduction higher than 55%. However, land retirement is the most costly among all the farm management alternatives. When there is no reliability requirement, it is not considered and thus does not affect agricultural profit under a low reduction target.

Table 3.3: Agricultural Profit under Restrictions (% Baseline Profit)

Reduction	**Reliability**	**A**	**B**	**C**	**D**	**E**
Average Targets	25%	103%	103%	103%	79%	103%
	35%	101%	100%	101%	67%	101%
	45%	97%	96%	97%	54%	97%
	55%	90%	88%	88%	40%	89%
	65%	69%	68%	65%	25%	n.a.
	75%	39%	39%	36%	6%	n.a.
	85%	4%	4%	2%	-15%	n.a.
Reliability Targets, 70% Robust	25%	58%	58%	56%	40%	n.a.
	35%	45%	45%	43%	31%	n.a.
	45%	32%	31%	30%	21%	n.a.
	55%	18%	17%	16%	9%	n.a.
	65%	3%	2%	1%	-4%	n.a.
	75%	-14%	-14%	-15%	-18%	n.a.
	85%	-37%	-37%	-37%	-37%	n.a.

Note: A: All farm management alternatives are available. B: Non-cropland cannot be converted to cropland. C: No reduced fertilizer or its combinations are allowed. D: No cover crop or its combinations are allowed. E: Cropland cannot be retired, i.e. converted into forest or prairie.

3.5 Considerations on Margin of Safety

A Total Maximum Daily Load (TMDL) is like a "pollution budget", which calculates the maximum of a pollutant that a water body can absorb, and allocates necessary portions of reduction to different pollution sources. A number of TMDL projects have been developed to control nutrient pollution, e.g., Lake Thunderbird in Oklahoma, Minnehaha Creek and Hiawatha in Minnesota, and the Animas River in New Mexico.[9]

Mathematically, a TMDL equals to the sum of point source loading allocation, nonpoint source loading allocation and a margin of safety.[10] A portion of the TMDL is reserved for a margin of safety to account for the effect of uncertainty on pollution control. The pollutant loads that are allocated to point and nonpoint sources are therefore smaller than the TMDL. Walker (2003) partitions a margin of safety into a margin of uncertainty, which accounts for prediction error caused by limitations of data and models, and a margin of variability, which refers to environmental variability that determines the frequency of meeting a reduction target. Considering the definition and the purpose of a margin of safety, especially a margin of variability, it is closely related to the reliability problem of pollution control in this paper.

While Franceschini and Tsai (2008) and Hantush (2009) point out that the values of margins of safety should take into account the reliability level or probability that a water quality target is met, margins of safety are not well designed in current TMDL projects (Dilks and Freedman, 2004). There is no clear rule or guidance on how reliability of pollution control or uncertainty should be incorporated into the calculation of margins of safety in existing TMDLs. For example, Zhang and Yu (2004) find that a margin of safety typically ranges from 5% to 10% of a TMDL load, although sometimes the range could be 5% to more than 40% (Minnesota Environmental Protection Agency, nd). In the Midwest (EPA Region 5 and 7), the most common margin of safety is 10% TMDL. More details are available in the appendix. Almost all margins of safety are subjectively chosen and are unable to reflect the reliability requirements of reduction targets (Dilks and Freedman, 2004; Zhang and Yu, 2004).

[9] Details of these TMDL projects can be found on the website www.epa.gov/tmdl/impaired-waters-and-nutrients.

[10] A margin of safety can be implicit, which is incorporated into a TMDL analysis via conservative assumptions. It can also be explicit, which is expressed as a portion of loading in a TMDL. In this paper, I focus on the explicit margin of safety.

Table 3.4: Mapping between Margins of Safety and Reliability levels, Robust

TMDL	**Reliability Level**				
	50%	**60%**	**70%**	**80%**	**90%**
75%	38%	41%	45%	49%	54%
65%	33%	36%	39%	42%	47%
55%	28%	30%	33%	36%	40%
45%	23%	25%	27%	29%	32%
35%	17%	19%	21%	23%	25%
25%	12%	13%	15%	16%	17%
15%	7%	8%	8%	9%	n.a.

Note: TMDL in Column 1 and margins of safety in the right columns are expressed in % baseline pollutant load. TMDL reflects a reduced pollution target, and a margin of safety reflects the requirement on reliability of pollution control. The pollutant loads allocated to point and nonpoint sources equal to the TMDL, subtracting the margin of safety.

By relating a margin of safety to a reliability target, Table 3.4 displays the improved margins of safety in the Wolf Creek Watershed. For example, in a TMDL project which restricts pollution to 55% baseline load with 70% reliability level, Table 3.4 shows that the margin of safety should be 33%. In other words, pollution from point and nonpoint sources should not exceed 22% baseline load. The value of the margin of safety increases with a stricter reliability requirement, as it is more difficult to achieve a reduction at a higher reliability level. The value also decreases with a lower TMDL, as the corresponding space for additional abatement is smaller. Compared with a fixed-value or a fixed-TMDL ratio margin of safety, the improved margin of safety provides a more precise value to meet a reliability target. The improved margins of safety are mostly higher than current margins of safety. If there is more specific information on the probability distribution of pollution, the improved margins of safety could be lowered. Figure 3.11 shows the difference between agricultural profits of a cost-effective solution and the improved margin of safety. The spatial allocation of farm-management practices is different under these two scenarios, but the difference in agricultural profits is small relative to the baseline agricultural profit. This difference in agricultural profits also decreases with a higher reduction target.

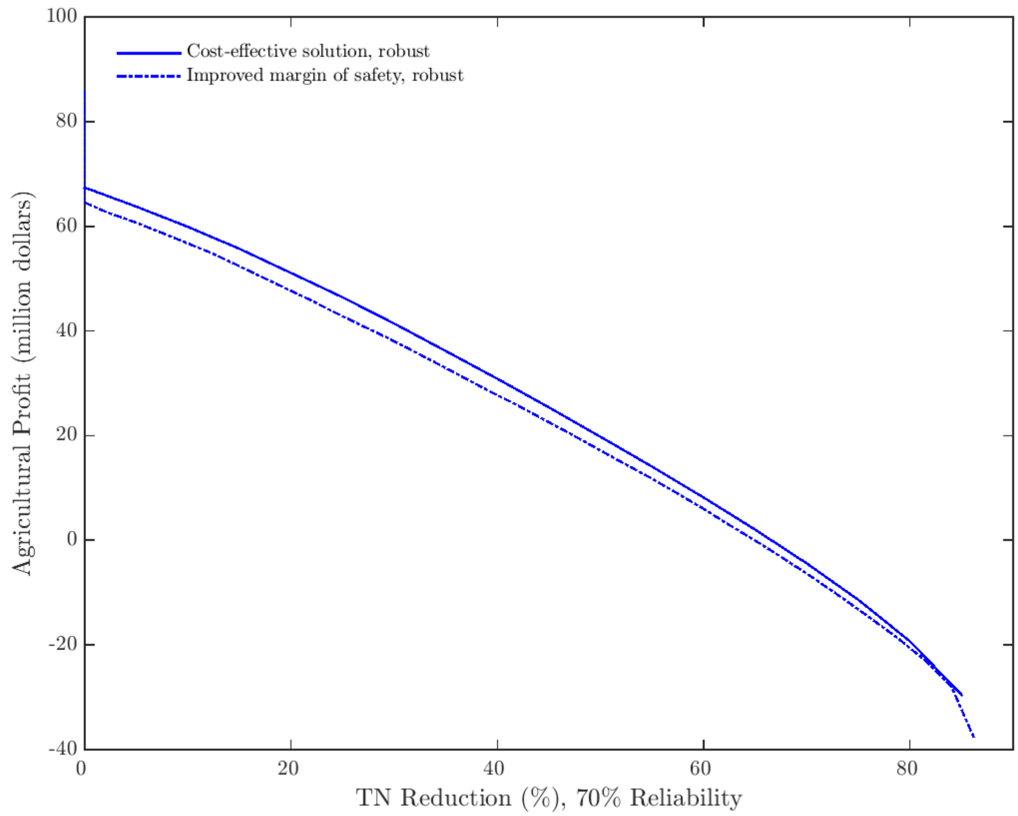


Figure 3.11: Agricultural Profit under Cost-Effective Solutions and Improved MOS

3.6 Discussion

The motivation for this paper is to analyze the reliability problem of agricultural runoff control. As discussed earlier, I consider the impact of farm management practices as well as their spatial allocation on the probability distribution of agricultural runoff and improve a robust abatement solution by employing a better balance between pollution reductions and agricultural profits. Moreover, this paper argues that the margins of safety in TMDLs currently are not reasonably designed to reflect a reliability level of a reduction target. The values of margins of safety should be connected with different requirements on reliability and reduction.

The frequencies of meeting a reduction target are distinctive under an average target and under a reliability target. If setting an average target of 41% nitrogen reduction, there would be five years in 2004-2013 in which we cannot meet the 41% annual reduction, and the highest gap would be 2.1 million kilograms. If a reliability target with a requirement of 70% probability is used, there would only be one year in which we miss the annual reduction, with the gap being 0.3 million kilograms. When environmental damage is related mostly to peak flows, the actual damage will differ substantially (Bystrom et al., 2000). However, in most cases, the expected pollution damage is not clear because either the probability distribution of pollution or the pollution damage is little known. It is difficult to maximize the expected social welfare as usual. Segerson (1988) suggests using an average target for pollution, but this target is not satisfactory when the actual damage is not linear in pollution. Although its precise effect on the expected social welfare is not clear, a reliability target controls the upper bound of the expected damage of pollution. The expected social welfare is thus protected by a lower bound.

Compared with an average target, a reliability target changes the traditional way of how water quality is managed. It directly caps the probability of failure to meet a reduction target, and highlights the water quality management which limits the occurrence of heavy runoff. As many studies predict under climate change, the higher temperature in aquatic systems in the future is likely to favor algal bloom, and the higher frequency of extreme weather events like heavy rainfall might make nutrients and sediments more easily washed off from the land. Under increasing environmental uncertainty, it is significant and necessary to consider reliability of pollution control in water quality management.

A reliability target is costly to achieve nonetheless, since it requires more abatement effort to prevent the worst runoff events from occurring. While I have not yet discussed the consequent damages of agricultural runoff or the benefits of runoff reductions in this paper, it does not mean that they are negligible (compared with abatement costs) for policymakers to set a reasonable reliability target. Eutrophication of the United States freshwater, as Dodds et al. (2009) compute, degrades lake-front property ($0.3 billion - $2.8 billion per year) and recreational water usage ($1 billion per year), harms the living of threatened and endangered species ($44 million per year), and affects the quality of drinking water ($813 million per year). More damages also lie in the negative effect of agricultural runoff on marine ecosystem, flood control, ecosystem services and public health (e.g. Diaz and Rosenberg, 2008; Martin, 1999). Brink and van Grinsven (2011) give an estimate of health costs from ecosystem impacts via N-runoff, €5-20/kg N. Combining the potential damage as well as the benefits, policymakers can make a reasonable judgment on target setting for agricultural runoff.

Still, the actual costs of reliable reductions would be lower than the estimates in this paper, if cover crops could be properly managed to achieve yield gains of crops, or if the market for forest, timber, and grass is well-established so that the economic values of forests and prairie can be realized. Moreover, there are two important practices which have not been discussed in the paper: controlled tile drainage and nutrient management, such as split application. These practices could reduce the nutrient runoff, and more importantly decrease the variation of nutrient runoff effectively. Farmers may change the timing and the quantity of fertilizer application and runoff in the tile, depending on the weather and other environmental changes they observe in the same period. These practices are most likely to decrease the cost of reliable reductions. In addition, with more information on the probability distribution of agricultural runoff, the abatement cost could be reduced further. Future research is needed to understand the relationship between abatement efforts and the variance of agricultural runoff. Iowa has already spent $235 million on the Environmental Quality Incentives Program in the period 1997-2015, $125 million on the Conservation Stewardship Program in 2011-2014, and almost $4 billion on the Conservation Reserve Program in 1995-2015. However, these might still be far from achieving a reliable reduction. More education and extension efforts are also needed, especially in the area which is less negatively affected by abatement.

Chapter 4

Reliability of Pollution Control, Implementation, and Asymmetric Information

4.1 Introduction

There is a degree of stochasticity in pollution under environmental uncertainty. The actual pollution may fluctuate widely in different years. For example, annual nitrogen runoff, including both nitrite and nitrate, from the Mississippi-Atchafalaya River Basin varied from 0.5 million to 1.6 million metric tons in the period of 1979-2014 (United States Geological Survey, 2015). A large literature on pollution control either neglects environmental uncertainty in the analysis or takes an average target on the pollution over time, which avoids considering the fluctuation in different periods. Segerson (1988) suggests using an average target for pollution control, especially when the benefits of pollution abatement are unknown. However, considering the stochastic nature of the pollution, an average target fails to consider the fat tail problem of the pollution probability distribution, where the most serious environmental damage occurs during extreme pollution events. This type of target embeds two disadvantages in pollution control: first, it cannot directly regulate the probability of failure to achieve a given pollution reduction; second, it cannot directly count a decline in the occurrence of heavy pollution events as an environmental improvement. Thus, it cannot properly describe the objective of pollution control under environmental uncertainty, that is, to improve the probability distribution of the pollution.

In order to better describe the objective of pollution control under environmental uncertainty, a reliability target and the concept of a reliable pollution reduction are introduced. A reliability target looks at a pollution reduction and also the probability that it is achieved under environmental uncertainty. Similarly, a reliable pollution reduction refers to a reduction which is not only about the reduction level but also about the probability that it is achieved under environmental uncertainty. In this sense, the first-best result of a reliability target for the total pollution in an area should consider each polluter's abatement effort and also how these abatement efforts collectively impact on the probability distribution of the total pollution. To figure out this result, the regulator needs intensive information on polluters' abatement practices and costs.

However, asymmetric information commonly exists in pollution control in practice. We may be unable to observe polluters' behaviors or to obtain the accurate information on their abatement costs. The unobservability of polluters' behaviors generates the moral hazard problem. Take agricultural runoff problem as an example, farmers may apply more fertilizer than what they report to the regulator. The lack of polluters' information on abatement costs prevents us from deriving the first-best outcome of a reliability target for pollution control. We need to address these problems caused by asymmetric information, so as to realize the first-best outcome of a reliability target.

The unobservable behavior problem can be solved by the instruments which are based on the consequent pollution. A Pigouvian tax is a typical tool in pollution control, when emission of each polluter is easily monitored. When it is not, for example, in nonpoint pollution diffuse sources make accurate metering of emission from each polluter prohibitively costly (Shortle and Horan, 2002), Segerson (1988) solves this nonpoint pollution problem by developing a tax/subsidy based on the ambient pollution, i.e. an ambient tax/subsidy. Although Xepapadeas (1995) attempts to mix a Pigouvian tax and an ambient tax to gradually transform a nonpoint source into a point source where individual emissions become easily monitorable, the idea of an ambient tax/subsidy is widely taken in nonpoint pollution control. Under this scheme, everyone is subject to an amount of tax or subsidy depending on the deviations of the total pollution from a given pollution level. Regardless of the observability of their behaviors, the optimal decisions of farmers will coincide with the optimal solution to pollution control, when the ambient tax/subsidy rate is properly determined. Segerson and Wu (2006) and Suter et al. (2010) further incorporate this ambient tax as a threat in the voluntary approach, which is triggered by the failure to meet a given pollution level, so as to induce the first-best outcome of pollution control. Polluters, who are faced with this threat, will comply with conservation practices accordingly. Xepapadeas (1991) extends Segerson's work in a dynamic environment and suggests a combination of fines and subsidies to induce the optimal result. Hansen (1998) also proposes a damage-based tax on the total pollution, when the environmental damage function is known. These incentive schemes all work to solve the moral hazard problem caused by polluters' unobservable actions and their undetectable emissions. However, when the environmental damage function is unknown, which is true in this paper, complete information on polluters' abatement costs is indispensable to determine the appropriate tax/subsidy rate so as to attain the first-best outcome of nonpoint pollution control.

The private information problem can be solved through mechanism design. The work of Vickrey (1961), Clarke (1971), and Groves (1973) together creates the Vickery-Clarke-Groves (VCG) auction mechanism, where every participant has an incentive to reveal their private information truthfully. Dasgupta et al. (1980) adapt the VCG mechanism in pollution control and develop an emission tax to minimize the sum of damage and the total abatement cost. Duggan and Roberts (2002) designs a truth-telling mechanism to achieve the first-best result of pollution control, where polluters choose the amount of permits to purchase at a price independent of their actions but they need to report their neighbor's emission level. If individual emission or individual use of a common property resource is detectable, Montero (2008) improves the work of Duggan and Roberts by incorporating the VCG-payoff structure in permit market, where each participant only claim his own demand schedule. Polasky et al. (2014) extend the application of the VCG mechanisms into the optimal provision of ecosystem services, where the benefits are spatially dependent. These mechanisms all motivate truthful revelation, and attain the optimal outcome in environmental conservation. However, all these mechanisms assume that everyone's behavior, emission or use of a resource is observable.

This paper contributes to the literature by developing an auction mechanism to achieve the first-best result of pollution control, where polluters have both private information and unobservable actions. Inspired by the literature on truth-telling mechanisms, we develop an auction where every polluter submits his subsidy bids on how much he needs to implement each conservation practice respectively and every polluter will receive a subsidy independent of his bids. A dominant strategy in this auction for polluters is to bid their actual abatement costs. Considering the moral hazard problem, polluters may deviate from the conservation practice which he is subsidized to do, whenever the practice is unobservable. In order to solve this problem, take fertilizer application as an example, we first limit the degree of unobservability by subsidizing only the minimum fertilizer rate that farmers may consider in an area, and then incorporate a fine/reward based on the total pollution into the auction. This fine/reward will be imposed on the farmers who are subsidized to minimize their fertilizer application, and ensures that it is optimal for these farmers not to deviate. This subsidy auction can obtain the actual information on polluters' abatement costs, so that the regulator is able to derive and to motivate polluters to achieve the first-best outcome of a reliability target for pollution control.

The paper is organized as follows. Section 2 discusses a reliability target in pollution control under environmental uncertainty. Section 3 analyzes the unobservable action problem and the private information problem in the implementation of pollution control. It introduces a subsidy auction to solve these problems. Section 4 uses the Wolf Creek Watershed as a study area and examines the implementation of a reliability target under asymmetric information. Section 5 concludes.

4.2 Reliability Targets

The objective of pollution control under environmental uncertainty is to improve the probability distribution of pollution. A reliability target is better from this perspective than a commonly-used average target, because it looks at a decline in the frequency of heavy pollution, and directly regulates the probability of fulfilling a reduction task of pollution. The most serious environmental damage occurs during the heavy pollution events. There are N farmers in the area. Each chooses how to manage its own land parcel. The regulator creates a list of best management practices (BMPs) of agricultural pollution management for farmers. The binary vector $\boldsymbol{x_i} = (x_i^1, x_i^2, ..., x_i^K)$ describes a farmer's decision regarding these farm-management options, where $x_i^k = 1$ means that farmer i chooses the farm-management alternative indexed k. The binary matrix $\boldsymbol{X} = (\boldsymbol{x_1'}, \boldsymbol{x_2'}, ..., \boldsymbol{x_N'})$ describes the farm-management practices in the whole area. Define a target level of pollution as $\bar{R}$ and a maximum probability of failure as α. Under a reliability target, the regulator solves Problem (4.1):

$$\max_{\boldsymbol{X}} \sum_{i=1}^{N} \mathbb{E}\left(\pi_i(\boldsymbol{x_i}, \boldsymbol{\epsilon})\right) \qquad \text{s.t. } \mathbb{P}(R(\boldsymbol{X}, \boldsymbol{\epsilon}) \geq \bar{R}) \leq \alpha, \tag{4.1}$$

where π_i is farmer i's profit, R is total pollution, and $\boldsymbol{\epsilon}$ is environmental uncertainty involving temperature, precipitation and the other stochastic factors. The computation of farmers' profits and the total pollution takes account of spatial heterogeneity.

The solution to Problem (4.1) focuses on the effect of different farming practices not just on the expectation of total pollution but on its probability distribution. For example, when a farmer applies conservation tillage or builds grassed waterway, he has the expected losses in profit. Influenced by slopes and soil conditions, these two farm-management alternatives generate the same expected abatement but different variances of total pollution. The one with a smaller variance of total pollution is preferred in the solution to Problem (4.1). If grassed waterway leads to a slightly lower abatement in the expected total pollution but a much higher reduction in the variance of total pollution, it may still be preferred in the solution to Problem (4.1). Moreover, this characteristic of the solution indicates that a single linear emission tax is not sufficient to achieve the first-best outcome of meeting a reliability target, because it cannot distinguish among farm-management alternatives which have the same expected abatement cost, the same expected reduction in total pollution but different variances of total pollution. We may also find that the marginal expected abatement cost is not necessarily the same across the area in the solution to Problem (4.1).

The marginal contribution of a farmer to a reliable reduction in the total pollution is determined not only by the farmer's action but also by the others' actions. A reliable reduction refers to a reduction that keeps the total pollution below some level with a specific reliability level, i.e. $1 - \alpha$ in the present paper. Mathematically, it is the abatement effort a in $\mathbb{P}\left(R^0 - R(\boldsymbol{x}, \boldsymbol{\epsilon}) \geq a\right) \geq 1 - \alpha$, where R^0 is the expectation of unregulated total pollution. A reliable reduction relates one's effort to its contribution of meeting a reliability target. Moreover, the marginal contribution of a farmer to a reliable reduction in the total pollution is influenced by the other farmers, because all farmers collectively change the probability distribution of total pollution. Take agricultural nutrient runoff as an example. It is likely to be higher in flooding years yet lower in drought years. If the current array of farm-management practices in the whole area leads to a larger deviation of nutrient runoff relative to its average level in flooding years, a farmer's marginal contribution to a reliable reduction a is more challenging, because it is more demanding to achieve a in flooding years. If the current farm-management practice in the whole area generates a smaller deviation of total pollution in flooding years, the farmer may contribute to a higher reliable reduction.

4.3 Asymmetric Information and Implementation

There are two sources of asymmetric information in achieving a reliability target of pollution control. One comes from unobservable actions of farmers, and the other comes from private information on farmers' profits. The classical analysis of pollution control starts from complete information, which in this paper allows us to directly determine the proper farm-management practices of all land parcels in the whole area to meet a reliability target in an efficient way. This proper farm-management practices can be enforced either by direct regulation or by incentive schemes like subsidies. However, in practice it is often the case that we have to deal with at least one source of asymmetric information. If farmers have unobservable actions but their profit information is publicly known, there are studies on performance-based instruments that make it optimal for farmers to behave properly to arrive at the optimal level of pollution. In terms of non-point pollution control, Segerson (1988) proposes a tax based on the ambient pollution level. Under her scheme, since it is difficult to identify emissions of individual farmers, every farmer gets a tax punishment when the total pollution is high. This tax scheme has been later used as a threat to motivate farmers to voluntarily manage their farms in an efficient way, so as to attain the first-best result of pollution control (Segerson and Wu, 2006; Suter et al., 2010). Considering the financial strain of Segerson's tax for farmers, Xepapadeas (1991) extends Segerson's mechanism to a combination of penalties and subsidies. If farmers have private information about their profits but their actions are observable, a VCG mechanism can be used to drive truthful revelation of their private information. It disconnects one's bid from one's payment in the mechanism, and makes it optimal for participants to disclose their private information. With farmers' accurate profit information, the regulator can determine the cost-effective way to meet a reliability target.

While several studies have dealt with either source of asymmetric information, we need to solve the problem of asymmetric information in terms of meeting a reliability target when both sources exist simultaneously. This paper contributes importantly to this question. We will first analyze, when their actions are not completely observable, how to motivate farmers to appropriately apply BMPs to meet a reliability target in an efficient way. Next, we will incorporate this analysis into an auction mechanism. This auction mechanism will be developed to attain the first-best outcome of Problem (4.1) under asymmetric information, where farmers' unobservable actions and their private information on profits both exist.

In the following section, we assume that the regulator prepares an agricultural BMP handbook which contains a list of BMPs. Farmers have rights to apply BMPs available in the handbook or not at all. This handbook specifies implementation details and requirements on all listed conservation practices: for example, the width of the grassed waterway, and the reduced amount of fertilizer application rate. In terms of reduced fertilizer application, we assume that the regulator sets the lowest application rate that farmers will consider in the area as required. It is also the unique unobservable BMP in the handbook. We will explain the reason for making this assumption in the analysis below.

4.3.1 Unobservability of Fertilizer Application

Fertilizer application is commonly considered in agricultural pollution control, but it is hardly observable. Normally, BMPs in agriculture are categorized into two groups. One is observable such as conservation tillage, cover crop, and grassed waterway, which make changes on the landscape and can be monitored. The other is unobservable, which is technically difficult or economically infeasible to detect. Reduced fertilizer application is a common non-structured BMP. We will focus on the asymmetric information problem caused by the unobservability problem of this BMP in the present paper.

Considering the unobservability of fertilizer application, we will discuss two methods to prompt farmers to use the appropriate amount of fertilizer as described in the BMP. Suppose that the regulator has figured out the solution $\boldsymbol{X^*}$ to Problem (4.1), which is a matrix with the row referring to farmers and the column referring to farm-management practices. He monitors farmers' use of the observable BMPs on their land parcels as indicated by $\boldsymbol{X^*}$. In order to meet a reliability target efficiently, because the regulator can observe all the other BMPs, the only question left is whether fertilizer application is reduced properly in the area. We introduce some notations before analyzing the two methods. Considering the two categories of BMPs, we convert $\boldsymbol{X^*}$ into two matrices. That is, $\boldsymbol{X^{*\prime}} = [\boldsymbol{X_A^{*\prime}}, \boldsymbol{X_B^{*\prime}}]$ where $\boldsymbol{X_A^*}$ is a matrix of the farmers whose farm-management practice is observable, and $\boldsymbol{X_B^*}$ corresponds to a matrix of the farmers who need to use less fertilizer. For farmers in group A, whether they comply with $\boldsymbol{X_A^*}$ is directly observable. For farmers in group B, their compliance with the reduced-fertilizer requirement is unclear. For example, if a farmer has to use less fertilizer and grow a cover crop in an efficient solution, we can only detect whether he grows a cover crop, but not his fertilizer application. Farm-management practices in $\boldsymbol{X_B^*}$ consist of two parts: one is observable BMPs, and the other is reduced fertilizer rate which is unobservable. We write the matrix $\boldsymbol{X_B^*} = [\boldsymbol{b_B^*}, \boldsymbol{r_B^*}]$, where $\boldsymbol{b_B^*}$ is group B farmers' decisions on observable BMPs with the row referring to farmers and the column referring to BMPs, and $\boldsymbol{r_B^*}$ describes these farmers' decisions reduced fertilizer rate with the row referring to farmers and the column referring to fertilizer rate. Given that all farmers implement observable BMPs properly on their land parcels, to achieve the first-best outcome of Problem (4.1), we shall make sure $\boldsymbol{r_B} = \boldsymbol{r_B^*}$.

The first method of inducing $\boldsymbol{r_B} = \boldsymbol{r_B^*}$ requires complete information on farmers' profits $\mathbb{E}\left(\pi_i(\boldsymbol{x_i}, \boldsymbol{\epsilon})\right)$, and it is a tax/subsidy on farmer group B, which is based on the total pollution in the whole area. The regulator also knows how different farming practices influence the expected total pollution. For each farmer in group B, we compute an ambient tax/subsidy rate suggested by Segerson (1988):

$$t_i = \frac{\mathbb{E}\left(\pi'_{r_i}\left([\boldsymbol{b_{Bi}^*}, r_{Bi}^*], \boldsymbol{\epsilon}\right)\right)}{\mathbb{E}\left(R'_{r_i}(\boldsymbol{X^*}, \boldsymbol{\epsilon})\right)}.$$

Since the marginal expected loss in profit is unlikely equal everywhere in an efficient solution to a reliability target, this tax/subsidy rate may be different among farmers and $t_i > 0$. If the total pollution is higher than $\mathbb{E}(R(\boldsymbol{X^*}, \boldsymbol{\epsilon}))$, farmers in group B will pay taxes. Otherwise, farmers in group B will receive subsidies. By imposing these differential tax/subsidy rates on farmers in group B, these farmers will be faced with Problem (4.2):

$$\max_{r_i} \mathbb{E}\left(\pi_i\left([\boldsymbol{b^*_{Bi}}, r_i], \boldsymbol{\epsilon}\right) - t_i\left(R(r_i) - \mathbb{E}(R(\boldsymbol{X^*}, \boldsymbol{\epsilon}))\right)\right), \tag{4.2}$$

where R is the total pollution influenced by farmer i's fertilizer application rate r_i. Assume that $\mathbb{E}(\pi'_{r_i}) > 0$, $\mathbb{E}(\pi''_{r_i}) < 0$, $\mathbb{E}(R'_{r_i}) > 0$, and $\mathbb{E}(R''_{r_i}) \geq 0$. A farmer's optimal solution under this tax/subsidy rate is r^*_{Bi}, and the optimal payoff of the farmer in Problem (4.2) is $\mathbb{E}\left(\pi_i\left(\boldsymbol{x^*_{Bi}}, \boldsymbol{\epsilon}\right)\right)$.

The second method is similar to Segerson's ambient tax/subsidy, but it does not require information on farmers' profits. It is a fine/reward on farmers in group B, which is also based on the total pollution. The regulator knows how different farming practices influence the probability distribution of total pollution. The method works as follows: When the total pollution does not exceed $\bar{R}$, every farmer in group B will receive a reward g; when the total pollution exceeds $\bar{R}$, every farmer in group B will receive a fine q. The relationship between the fine and the reward is $g/q = \alpha/(1-\alpha)$, and their values are sufficiently high.[1]

Farmers in group B are faced with Problem (4.3):

$$\max_{r_i} \mathbb{E}\left(\pi_i\left([\boldsymbol{b^*_{Bi}}, r_i], \boldsymbol{\epsilon}\right)\right) + F(\bar{R})g - (1 - F(\bar{R}))q, \tag{4.3}$$

where F is the cumulative distribution function of total pollution, which is influenced by r_i. As long as $F(\bar{R}) = 1 - \alpha$ is achieved, the expected sum of the fine and the reward is zero, i.e. $F(\bar{R})g - (1 - F(\bar{R}))q = 0$. Assume that $\mathbb{E}(\pi'_{r_i}) > 0$ and $F'_{r_i}(\bar{R}) < 0$. By setting sufficiently high g and q, the objective function has a negative first derivative. Because $\boldsymbol{r^*_B}$ in the agricultural BMP handbook is set at the minimum fertilizer application rate that farmers will consider , farmer i's optimal solution to Problem (4.3) is r^*_{Bi}, and the optimal payoff the the farmer in Problem (4.3) is $\mathbb{E}\left(\pi_i\left(\boldsymbol{x^*_{Bi}}, \boldsymbol{\epsilon}\right)\right)$.[2] If $\boldsymbol{r^*_B}$ is not the minimum fertilizer application rate in the area, farmers may deviate from using

[1] Mathematically, $g = \dfrac{\alpha}{1-\alpha} q \geq \max_i \left\{ -\dfrac{\mathbb{E}\left(\pi'_{r_i}\left([\boldsymbol{b^*_{Bi}}, r^*_{Bi}], \boldsymbol{\epsilon}\right)\right)}{F'_{r_i}(\bar{R})} \right\}$.

[2] See the proof in Appendix.

$\boldsymbol{r_B^*}$. They may over reduce their fertilizer application for the purpose of obtaining a net expected reward by reaching $\mathbb{P}(R(\boldsymbol{x}, \boldsymbol{\epsilon}) \geq \bar{R}) < \alpha$. This does not result in failure of meeting a reliability target, but it affects whether this target is achieved in an efficient way.

Depending on whether farmers' profit information is required or not, the above discusses two methods that make it optimal for farmers in group B to reduce their fertilizer application to $\boldsymbol{r_B^*}$. These methods prevent moral hazard of farmers in their fertilizer application. Particularly, the fine/reward method can be incorporated in a subsidy auction mechanism which will be discussed next. It ensures that farmers do not deviate from the requirement on reduced fertilizer application in the BMP if they are subsidized to do so.

4.3.2 Private Information on Profits

In the presence of private information on farmers' profits, we need to develop a policy that prompts farmers to truthfully reveal their profits. Inspired by the auction mechanism of Polasky et al. (2014), we now develop an auction mechanism under asymmetric information on farmers' profits and their unobservable fertilizer application. Since "carrots" have been historically used in agricultural pollution control in the United States, we will use a subsidy auction in the following, where farmers submit bids on subsidies which they need to implement BMPs (Segerson and Wu, 2006). We will prove that this subsidy auction is a truth-telling mechanism that can attain the first-best outcome of meeting a reliability target.

We define some notations here. Each farmer has his optimal unregulated practice x_i^0, and a number of abatement practices in the agricultural BMP handbook. Farmer i's opportunity cost for farm-management practice x_i^k is private information, and it is $c_i^k = \mathbb{E}(\pi_i(x_i^0, \boldsymbol{\epsilon})) - \mathbb{E}(\pi_i(x_i^k, \boldsymbol{\epsilon}))$. Denote $\boldsymbol{c_i} = (c_i^0, c_i^1, ..., c_i^K)$, where each element in $\boldsymbol{c_i}$ stands for the cost of applying a single BMP like growing a cover crop, or a combination of BMPs such as growing a cover crop and reducing fertilizer. The regulator attempts to minimize total cost to achieve an exogenously given reliability target $\mathbb{P}(R \leq \bar{R}) \geq 1-\alpha$. The regulator faces Problem (4.4), which is essentially the same as Problem (4.1):

$$\min_{\boldsymbol{X}} \sum_{i=1}^{N} \boldsymbol{c_i x_i} \qquad \text{s.t. } \mathbb{P}(R(\boldsymbol{X}, \boldsymbol{\epsilon}) \leq \bar{R}) \geq 1 - \alpha. \tag{4.4}$$

When information on $\boldsymbol{c_i}$ is not publicly known, we introduce a truth-telling auction in the following. The regulator commits to a subsidy policy which involves a fine/reward scheme on the farmers who will be subsidized to reduce their fertilizer. Every farmer submits a series of subsidy bids to cover its cost on different farm-management practices. The regulator, based on all bids, computes and determines which bids to accept and which to reject. Assume that $\mathbb{E}(\pi'_{r_i}) > 0$ and $F'_{r_i}(\bar{R}) < 0$ for every farmer i. This assumption is reasonable because an increase in fertilizer application is likely to increase a farmer's profit and also a higher probability of heavy pollution. Also, assume that there is no cooperation among farmers. Each farmer bids simultaneously and independently. The details of a subsidy auction are as follows:

Step 1: The regulator provides an agricultural BMP handbook to farmers which entails the implementation details and requirements on all listed BMPs. Reduced fertilizer is the only unobservable BMP, and the required fertilizer application is set at the minimum fertilizer application rate that farmers will consider in the area.[3]

The regulator also announces the policy on subsidy payment: At most one bid from a farmer will be accepted. If a farmer's bid is accepted and consists only of observable BMPs, the regulator will directly pay him a subsidy. If a farmer's bid is accepted and includes a practice involving reduced fertilizer, the regulator will pay him a subsidy and also impose a fine/reward on this farmer described as the second method in Section 3.1. If all of a farmer's bids are rejected, he will receive no subsidy.

Step 2: Each farmer simultaneously submits a series of bids $\boldsymbol{s_i} = (s_i^0, s_i^1, ..., s_i^K)$, where each element refers to a bid on an individual BMP or a combination of different BMPs.

Step 3: The regulator collects all bids. For each farmer i and each of his conservation farm-management practice x_i^k, the regulator solves the two problems below. The first problem assumes that farmer i implements x_i^k:

$$TC_i^{k**} = \min_{\boldsymbol{X}} s_i^k + \sum_{j \neq i} \boldsymbol{s_j x_j} \qquad \text{s.t. } \mathbb{P}(R(\boldsymbol{X}, \boldsymbol{\epsilon}) \leq \bar{R}) \geq 1 - \alpha. \tag{4.5}$$

[3] This condition is used to prove that truth-telling is a dominant strategy in the auction mechanism. It prevents farmers from underbidding and over-reducing their fertilizer application to pursue a net expected reward under the fine/reward scheme. However, lack of this condition does not result in failure to meet a reliability target or achieve a given reliable pollution reduction.

The solution to Problem (4.5) is $\boldsymbol{X_i^{k**}} = (\boldsymbol{x_{1,i}^{k**}}, \boldsymbol{x_{2,i}^{k**}}, ..., \boldsymbol{x_{N,i}^{k**}})$, where $\boldsymbol{x_{i,i}^{k**}}$ has $x_{i,i}^{k**} = 1$.

The second problem assumes that farmer i does not make any abatement effort, i.e. implements his unregulated optimal practice:

$$TC_{\text{-}i}^{**} = \min_{\boldsymbol{X}} \sum_{j \neq i} \boldsymbol{s_j x_j} \qquad \text{s.t. } \mathbb{P}(R(\boldsymbol{X}, \boldsymbol{\epsilon}) \leq \bar{R}) \geq 1 - \alpha. \tag{4.6}$$

The solution to Problem (4.6) is $\boldsymbol{X_{\text{-}i}^{**}} = (\boldsymbol{x_{1,\text{-}i}^{**}}, \boldsymbol{x_{2,\text{-}i}^{**}}, ..., \boldsymbol{x_{N,\text{-}i}^{**}})$, where $\boldsymbol{x_{i,\text{-}i}^{**}}$ has $\sum_{k=1}^{K} x_{i,\text{-}i}^{k**} = 0$.

Step 4: The regulator calculates the potential payment p_i^k to farmer i when the farmer applies x_i^k:

$$p_i^k = TC_{\text{-}i}^{**} - \sum_{j \neq i} \boldsymbol{s_j x_{j,i}^{k**}}.$$

Step 5: If $p_i^k < s_i^k \ \forall k \in \{1, 2, ..., K\}$, the regulator will reject farmer i. Farmer i will receive no subsidy and apply the unregulated optimal practice. If $\exists k \in \{1, 2, ..., K\}$ such that $p_i^k \geq s_i^k$, the regulator will accept farmer i's bid k^* where $k^* = \text{argmax}_{k \in \{1,2,...,K\}}(p_i^k - s_i^k)$. If there are multiple k^*, the regulator will randomly choose one of them. Farmer i will be subsidized to implement $x_i^{k^*}$. When $x_i^{k^*}$ is observable, this farmer will receive a payment $p_i^{k^*}$. When $x_i^{k^*}$ is unobservable, he will receive a payment $p_i^{k^*}$ and will also be subject to a fine/reward based on the total pollution as described in Section 3.1.

4.3.3 Properties of Subsidy Auctions

The subsidy auction above has a VCG payoff structure, which creates a disconnect between a farmer's bid and the subsidy received by this farmer. The value of $\boldsymbol{p_i} = (p_i^1, p_i^2, ..., p_i^K)$ is not determined by farmer i's bids $\boldsymbol{s_i}$. A farmer's bid only determines whether his bid will be accepted by the regulator or not. Farmers do not know their contribution to a reliable reduction in the total pollution, which is also influenced by the other farm-management practices. They do not know the values of TC_i^{**} and $TC_{\text{-}i}^{**}$, either. The regulator collects farmers' bids to solve the problems in Step 3, and computes the final payment to each farmer. This amount of payment does not depend on a farmer's own bid, but on the bids from the other farmers. Farmers do not have incentives to lie about their costs.

Proposition 1. A dominant strategy for each farmer in this subsidy auction is to bid $\boldsymbol{s_i} = \boldsymbol{c_i}$.

Proof: There is no cooperation among farmers. They submit their bids simultaneously and have no idea about their effects in an efficient solution to meet a reliability target. Let's compute the payoff to each farmer when he submits $\boldsymbol{s_i} = \boldsymbol{c_i}$ and $\boldsymbol{s_i} \neq \boldsymbol{c_i}$. We shall prove that $\boldsymbol{s_i} = \boldsymbol{c_i}$ is a dominant strategy for farmers.

When a farmer bids $\boldsymbol{s_i} = \boldsymbol{c_i}$, there are two possible scenarios. (i) $p_i^k < c_i^k$ $\forall k \in \{1, 2, ..., K\}$. The regulator rejects farmer i, and this farmer receives no subsidy. The farmer will apply the unregulated optimal practice, and his payoff will be $\mathbb{E}(\pi_i(x_i^0, \boldsymbol{\epsilon}))$. (ii) $\exists k \in \{1, 2, ..., K\}$ such that $p_i^k \geq c_i^k$. The regulator will accept farmer i's bid k^* where $k^* = \text{argmax}_{k\in\{1,2,...,K\}}(p_i^k - c_i^k)$, and farmer i will receive $p_i^{k^*}$. Since $c_i^l = \mathbb{E}\left(\pi_i\left(x_i^0, \boldsymbol{\epsilon}\right)\right) - \mathbb{E}\left(\pi_i\left(x_i^l, \boldsymbol{\epsilon}\right)\right)$ and $p_i^{k^*} - c_i^{k^*} \geq p_i^l - c_i^l$ $\forall l \in \{1, 2, ..., K\}$, we have $\mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*} \geq \mathbb{E}\left(\pi_i\left(x_i^0, \boldsymbol{\epsilon}\right)\right)$ and $\mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*} \geq \mathbb{E}\left(\pi_i\left(x_i^l, \boldsymbol{\epsilon}\right)\right) + p_i^l$ $\forall l \in \{1, 2, ..., K\}$. When $x_i^{k^*}$ is observable, farmer i will have a payoff $\mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*}$. When $x_i^{k^*}$ is unobservable, he will face Problem (4.3) under a sufficiently high fine/reward. Since the minimum fertilizer application rate is the unique unobservable BMP here, $\mathbb{E}(\pi'_{r_i}) > 0$ and $F'_{r_i}(\bar{R}) < 0$, the preceding section has showed that the farmer's optimal decision is to use the minimum fertilizer as described in the BMP. The payoff of the farmer is $\mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*}$.

When a farmer bids $\boldsymbol{s_i} \neq \boldsymbol{c_i}$, it means that there exists at least one $l \in \{1, 2, ..., K\}$ such that $s_i^l > c_i^l$ (overbidding) or $s_i^l < c_i^l$ (underbidding). We discuss each case in the following.

Case 1: $s_i^l > c_i^l$. (i) $p_i^k < c_i^k$ $\forall k \in \{1, 2, ..., K\}$. The best payoff of farmer i bidding $s_i^l > c_i^l$ is $\mathbb{E}(\pi_i(x_i^0, \boldsymbol{\epsilon}))$. (ii) $p_i^l \geq c_i^l$. Denote $k^* = \text{argmax}_{k\in\{1,2,...,K\}}(p_i^k - c_i^k)$. If $l \neq k^*$, the best payoff that farmer i will have is $\mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*}$. If $l = k^*$, it is possible that $k_1 = \text{argmax}_{k\in\{1,2,...,K\}}(p_i^k - s_i^k)$ when $s_i^l > c_i^l$, and $k_1 \neq k^*$. The final payoff that farmer i will have is $\mathbb{E}\left(\pi_i\left(x_i^{k_1}, \boldsymbol{\epsilon}\right)\right) + p_i^{k_1} \leq \mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*}$. Thus, the payoff of bidding $s_i^l > c_i^l$ is no better than that of truthful revelation.

Case 2: $s_i^l < c_i^l$. (i) $p_i^k < c_i^k$ $\forall k \in \{1, 2, ..., K\}$. If $p_i^l < s_i^l$, the best payoff of farmer i bidding $s_i^l < c_i^l$ will be $\mathbb{E}(\pi_i(x_i^0, \boldsymbol{\epsilon}))$. If $p_i^l \geq s_i^l$, it may be the case that farmer i's payoff is $\mathbb{E}\left(\pi_i\left(x_i^l, \boldsymbol{\epsilon}\right)\right) + p_i^l \leq \mathbb{E}\left(\pi_i\left(x_i^0, \boldsymbol{\epsilon}\right)\right)$. (ii) $p_i^l \geq c_i^l$. Denote $k^* = \text{argmax}_{k\in\{1,2,...,K\}}(p_i^k - c_i^k)$.

If $l = k^*$, the best payoff that farmer i will have is $\mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*}$. If $l \neq k^*$, it is possible that $l = \text{argmax}_{k\in\{1,2,\ldots,K\}}(p_i^k - s_i^k)$ when $s_i^l < c_i^l$. The final payoff that farmer i will have is $\mathbb{E}\left(\pi_i\left(x_i^l, \boldsymbol{\epsilon}\right)\right) + p_i^l \leq \mathbb{E}\left(\pi_i\left(x_i^{k^*}, \boldsymbol{\epsilon}\right)\right) + p_i^{k^*}$. Hence, the payoff of bidding $s_i^l < c_i^l$ is no better than that of truthful revelation.

We conclude that the strategy $\boldsymbol{s_i} \neq \boldsymbol{c_i}$ is dominated by $\boldsymbol{s_i} = \boldsymbol{c_i}$. □

This proposition implies that because farmers' subsidies do not depend on their bids in the auction, any deviation from truthful revelation may make farmers unable to obtain their maximum payoffs, which are the payoffs they will get under truthful revelation for sure.

Besides truthful revelation, this subsidy auction can achieve the cost-effective result of Problem (4.4). Especially when farmers' impacts are correlated with each other on a reliable reduction in the total pollution, different farming practices by a farmer alter the marginal contribution of the other farmers to achieving a reliability target. Farmers disclose their actual costs and find it optimal not to deviate from the farm-management practice that they are subsidized for. The regulator can take advantage of this information to determine the cost-effective way to attain a reliability target. In order to implement the cost-effective farm-management practices, the regulator shall properly accept and reject farmers' bids on different farm-management practices.

Proposition 2. This subsidy auction can achieve a reliability target in an efficient way.

Proof: Proposition 1 shows that truthful revelation is a dominant strategy for farmers under this subsidy auction. With the accurate information on farmers' costs, we can figure out the efficient way to attain a reliability target, and the minimum total cost is:

$$TC^* = \min_{\boldsymbol{X}} \sum_{i=1}^{N} \boldsymbol{c_i x_i} \qquad \text{s.t. } \mathbb{P}(R(\boldsymbol{X}, \boldsymbol{\epsilon}) \leq \bar{R}) \geq 1 - \alpha.$$

The corresponding solution is $\boldsymbol{X^*}$. Obviously, $TC^* \leq TC_{\text{-}i}^{**}$ and $TC^* \leq TC_i^{k**}$ $\forall k \in \{1, 2, ..., K\}$. In order to prove Proposition 2, we need to show that: $\forall k \in \{1, 2, ..., K\}$, if $x_i^k = 1$ in $\boldsymbol{X^*}$, that is, $x_i^{k*} = 1$, the regulator will accept farmer i's bid on x_i^k and $p_i^k \geq c_i^k$; if $x_i^{k*} = 0$, the regulator will reject farmer i's bids, or will accept farmer i's bid on another farm-management practice.

For any $x_i^{k*} = 1$ where $k \in \{1, 2, ..., K\}$, farmer i should apply x_i^k on his land parcel in the efficient solution $\boldsymbol{X^*}$. Hence, $\boldsymbol{X^*} = \boldsymbol{X_i^{k**}}$, $TC^* = TC_i^{k**} \leq TC_{\text{-}i}^{**}$ and $TC_i^{k**} \leq TC_i^{l**}$ $\forall l \neq k$ and $l \in \{1, 2, ..., K\}$. Under truthful revelation, we have $p_i^l - c_i^l = TC_{\text{-}i}^{**} - TC_i^{l**}$ $\forall l \in \{1, 2, ..., K\}$. In this sense, $p_i^k - c_i^k = TC_{\text{-}i}^{**} - TC_i^{k**} \geq TC_{\text{-}i}^{**} - TC_i^{l**} = p_i^l - c_i^l$ $\forall l \in \{1, 2, ..., K\}$ and $p_i^k - c_i^k = TC_{\text{-}i}^{**} - TC_i^{k**} \geq 0$. Thus, the regulator accepts farmer i's bid on x_i^k and pays him $p_i^k \geq c_i^k$. Farmer i will apply x_i^k under this auction.

For any $x_i^{k*} = 0$ where $k \in \{1, 2, ..., K\}$, farmer i either applies another conservation farm-management practice or the unregulated optimal practice on its land parcel in the efficient solution $\boldsymbol{X^*}$. If farmer i applies the unregulated optimal practice in $\boldsymbol{X^*}$, then $\boldsymbol{X^*} = \boldsymbol{X_{\text{-}i}^{**}}$, $TC^* = TC_{\text{-}i}^{**} < TC_i^{l**}$ $\forall l \in \{1, 2, ..., K\}$. In this sense, $p_i^l - c_i^l = TC_{\text{-}i}^{**} - TC_i^{l**} < 0$ $\forall l \in \{1, 2, ..., K\}$. Thus, the regulator rejects farmer i's bids, and farmer i applies the unregulated optimal practice under this auction. If farmer i applies another conservation farm-management practices in $\boldsymbol{X^*}$, then there exists $l \neq k$ and $l \in \{1, 2, ..., K\}$ such that $TC_i^{l**} < TC_i^{k**}$ and $TC_i^{l**} \geq TC_{\text{-}i}^{**}$. Since $p_i^l - c_i^l = TC_{\text{-}i}^{**} - TC_i^{l**} >= TC_{\text{-}i}^{**} - TC_i^{k**} = p_i^k - c_i^k$ and $p_i^l - c_i^l \geq 0$, the regulator will reject farmer i's bid on x_i^k, and farmer i will be subsidized to implement another conservation farm-management practice under this auction.

In all, the efficient way to meet a reliability target is achieved under this auction. □

Figure 4.1 displays the intuition of Proposition 2. Based on the structure of subsidy in the auction, a farmer's payoff of applying practice l equals $TC_{\text{-}i} - TC^l$ under truthful revelation, where $TC_{\text{-}i}$ is the minimum total cost of all farmers to meet a given reliability target, and TC^l is the minimum total cost of all farmers to meet the same reliability target when this farmer applies practice l. According to the regulator's policy on farmers' bids, he essentially accepts the bid which generates the maximum payoff of a farmer. As long as practice l is in the first-best solution to a given reliability target, the regulator will accept the bid on this practice because it generates $TC^l = TC^*$, which is the minimum total cost of meeting the same reliability target.

Although asymmetric information creates difficulty in pollution control, the subsidy auction above can properly solve the unobservability problem of fertilizer application and private information problem of farmers' abatement costs to attain the reliability target in an efficient way.

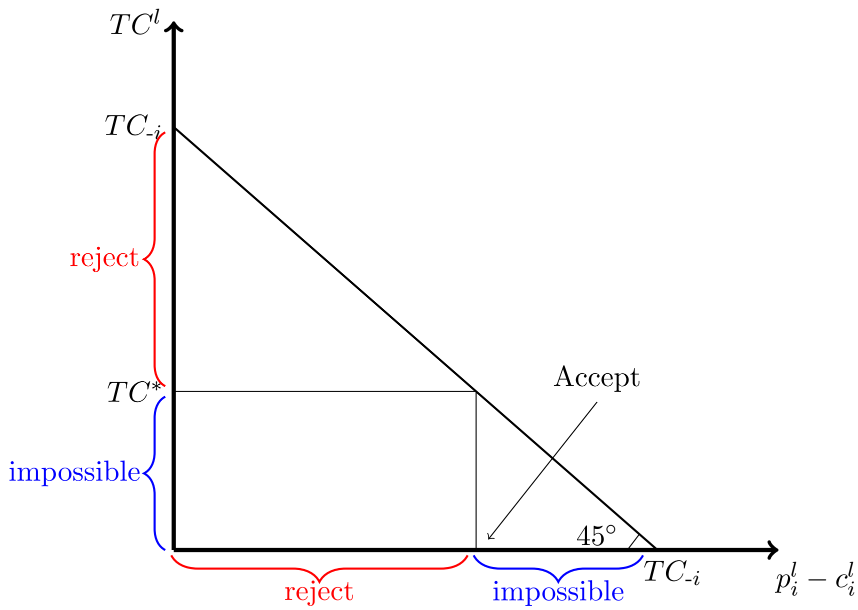


Figure 4.1: Proposition 2: Efficient Outcome of Pollution Control

4.3.4 Cooperation and Information Rent

Besides the strength of truthful revelation and attainment on the cost-effective result of a reliability target, the subsidy auction mechanism has two issues embedded, which Polasky et al. (2014) have also discussed in their study. The first is collusion among farmers in bidding. When farmers submit their bids independently, the subsidy auctions are proved to be truthful revealing. However, farmers may collude with each other, and thus deviate from truthful revelation to raise their total payoffs. Consider an example of two farmers with one abatement practice available. Each farmer is able to meet a reliability target on its own by applying its abatement practice. Suppose their unregulated expected optimal profits are both 10, and their expected profits of the abatement practice are 5. In a subsidy auction to meet this reliability target, when they bid 5 truthfully, they will have an equal chance of being accepted. These two farmers may collaborate in bidding higher, for example, in Table 4.1, for higher payoffs than truthful revelation.

Table 4.1: Farmers' Payoffs in A Subsidy Auction

	$s_2 = 7$	$s_2 = 5$
$s_1 = 7$	(1, 1)	(0, 2)
$s_1 = 5$	(2, 0)	(0, 0)

However, a collusive strategy among farmers may not be easy to sustain. Under a subsidy auction, farmers who overbid will take a risk of being rejected and losing the possible gains. Farmers who underbid may receive subsidies too small to cover their costs. Polasky et al. (2014) point out that this situation is similar to a Prisoner's Dilemma where each player has a dominant strategy to defect rather than cooperate, and to maintain successful cooperation is information-intensive. Particularly when there are numerous farmers and multiple BMPs available, it is essential to develop a strategy to prevent deviation from cooperation. To develop this strategy requires prediction of the regulator's decision and potential subsidy payment. In this sense, it is important to know farmers' private information on costs and also how different farm-management practice affects the probability distribution of total pollution.

The second issue is information rent, which refers to the difference between subsidies and abatement costs here. Under a subsidy auction above, a subsidy paid to a farmer depends on his contribution to a reliable reduction in the total pollution and the bids of the other farmers. It is at least as large as the farmer's actual cost. Therefore, the total subsidy is weakly greater than total cost. The attempt to close the gap between total subsidy and total cost will result in failure to meet the first-best outcome of Problem (4.4), because some farmers who could efficiently contribute to a reliable reduction in the pollution may end up quitting the conservation practices. Polasky et al. (2014) observe that information rent is an unavoidable feature which motivates farmers to reveal their private information. Telling truth is a dominant strategy of farmers only if the regulator commits to its subsidy policy. The regulator cannot later adjust the amount of subsidies to reduce the information rent, while expect that farmers keep truthful revelation.

4.4 Empirical Study

In the following, we will focus on the Wolf Creek Watershed in Iowa to analyze reliability of pollution control under asymmetric information. The Wolf Creek Watershed has a serious nitrogen runoff problem. It is located in the Middle Ceder Watershed, one of nine priority 8-digit Hydrological Unit Code watersheds of pollution control identified in the Iowa Nutrient Reduction Strategy. The Wolf Creek Watershed is 846 km^2 (327 square miles). About 83% of the area is cropland, and annual crop profit was $79.6 million from 2004 to 2013. The entire watershed is in No. 104 Major Land resource Area, according to its soil pattern, climate, water resources and land use (Natural Resources Conservation Service, nd). During the period from 2004 to 2013, an average of 2.3 million kilograms total nitrogen (TN) ran off this watershed annually, fluctuating from 0.6 million to 4.6 million kilograms.

Table 4.2: Abbreviations for Conservation Farm-Management Alternatives

Abbreviation	Farm-Management Alternative
Ct	Conservation tillage
Nt	No tillage
Gw	Grassed waterways
Rf	Reduced fertilizer (145 kg N/ha, 20.75 kg P/ha)[a]
Cc	Cover crop
Pr	Prairie
Fd	Forest
RN	Reduced fertilizer and No tillage
RC	Reduced fertilizer and Cover crop
NC	No tillage and Cover crop
RNC	Reduced fertilizer, No tillage, and Cover crop

a. Reduced fertilizer refers to the practice where nitrogen application rate is reduced by 10%, and phosphorus application rate is reduced by 17%.

This study uses the Soil and Water Assessment Tool (SWAT) to simulate the effect of different farming practices on crop production and nitrogen runoff. There are 11 farm-management alternatives to abate the pollution in the analysis, which are listed in Table 4.2. We assume that reduced fertilizer use is the minimum fertilizer rate that farmers will consider in the area. The implementation costs of different farm-management practices are obtained from studies on conservation practices in Iowa (Kling et al., 2007; Iowa State University Extension, 2013; Duffy and Calvert, 2015). The input costs and crop prices are inflation-adjusted average during 2011-2015 (The United States Department of Agriculture, 2016; Iowa State University Extension, 2013). We assume no market uncertainty in the analysis.

Reduced fertilizer application plays a role in the efficient solution to a reliability target in the whole watershed. There are 7,528 Hydrological Response Units (HRUs) in the Wolf Creek Watershed. An HRU is the basic unit on which SWAT runs simulations. It can be regarded as a land parcel with homogenous land use and soil conditions. Table 4.3 lists the number of HRUs that implement farm-management practices involving reduced fertilizer, i.e. Rf, RN, RC, and RNC, in the efficient solution to different reliability targets. For example, there are approximately 2,100 HRUs which need to reduce their fertilizer in order to efficiently meet a 30% reduction in the pollution with 70% reliability level. The use of reduced fertilizer is not trivial to attain a reliable reduction in a cost-effective way.

Table 4.3: Solving Unobservability of Fertilizer Application to Meet Different Reliability Targets, 70% Reliability Requirement

Reduction	**%HRU**	**Tax/Subsidy Rate ($/kg TN)**			**Fine/Reward ($1000)**	
		Range	**Mean**	**SD**	**Fine**	**Reward**
30%	28%	[1.71, 119.2]	37.7	17.7	338	145
35%	27%	[1.71, 119.2]	38.6	18.2	344	147
40%	25%	[1.71, 128.9]	39.7	18.6	343	147
45%	24%	[1.71, 132.4]	41.3	19.3	494	212
50%	23%	[1.71, 132.4]	42.5	19.8	529	227

Table 4.3 also describes two methods, tax/subsidy and fine/reward, that are related

to unobservability of fertilizer application. Continuing the example above, if we know farmers' cost information, we can compute the tax/subsidy rates for those 2,100 HRUs. These taxes/subsidies are based on TN running off the entire watershed. Whether they are taxes or subsidies depends on whether the total pollution is high or low. These tax/subsidy rates vary from area to area, since the marginal abatement costs differ across the watershed. By imposing these differential rates on the 2,100 HRUs, it is optimal for farmers on those land parcels to properly reduce their fertilizer as in the BMP. If we do not have farmers' cost information, we need to use a sufficiently high fine and reward to motivate proper fertilizer application on these land parcels. Whether it is a fine or a reward relies on whether a 30% reduction in the pollution relative to the unregulated total pollution is met or not. By enforcing the fine and the reward on those 2,100 HRUs at least as high as the values in Table 4.3, farmers on those land parcels will use less fertilizer, even though their fertilizer application is not observed by the regulator.

Table 4.4: Subsidy Auction to Meet A Reliability Target: 40% Reduction, 70% Reliability Requirement, One BMP ($1000)

HRU_ID	X^*	c_i	TC_i^{**}	TC_{-i}^{**}	p_i	$p_i - c_i$	**Accept**
11	Pr	12.1	69,787.7	69,795.1	19.4	7.3	Yes
12	Ac	14.0	69,792.8	69,787.7	0.0	-14.0	No
13	Ac	140.5	69,864.8	69,787.7	0.0	-140.5	No
14	Ac	181.8	69,815.0	69,787.7	0.0	-181.8	No
15	Pr	32.9	69,787.2	69,801.9	47.6	14.7	Yes
16	Pr	53.3	69,787.7	69,801.0	66.6	13.3	Yes

Table 4.4 gives examples of how a subsidy auction works under asymmetric information. For simplicity, this table discusses the scenario where farmers have only one abatement practice: converting cropland into prairie, the full suite of BMPs will be considered in a moment. We want to achieve a 40% reduction in the pollution with 70% reliability level efficiently in the subsidy auction. The auctions run on the scale of all HRUs in the watershed. Every HRU submits a bid on Prairie at the same time. We only

list the results of HRU_ID 11-16 here for parsimony. Take HRU_ID 11 as an example. In the efficient solution to meet the target, this HRU should convert its cropland to prairie. The minimum total cost of the efficient solution is around $70 million. If this HRU does not retire the land, the minimum total cost will be higher to meet the target. The difference between the two costs determines the potential subsidy $19,400 to the farmer on HRU_ID 11. Since farmers disclose their costs in the subsidy auction, the regulator accepts the bid. The farmer on HRU_ID 11 earns a surplus of $7,300, which is its information rent. Similarly, for the rest of HRUs, the regulator accepts the bids when $TC_i^{**} \leq TC_{-i}^{**}$, and rejects them when $TC_i^{**} > TC_{-i}^{**}$.

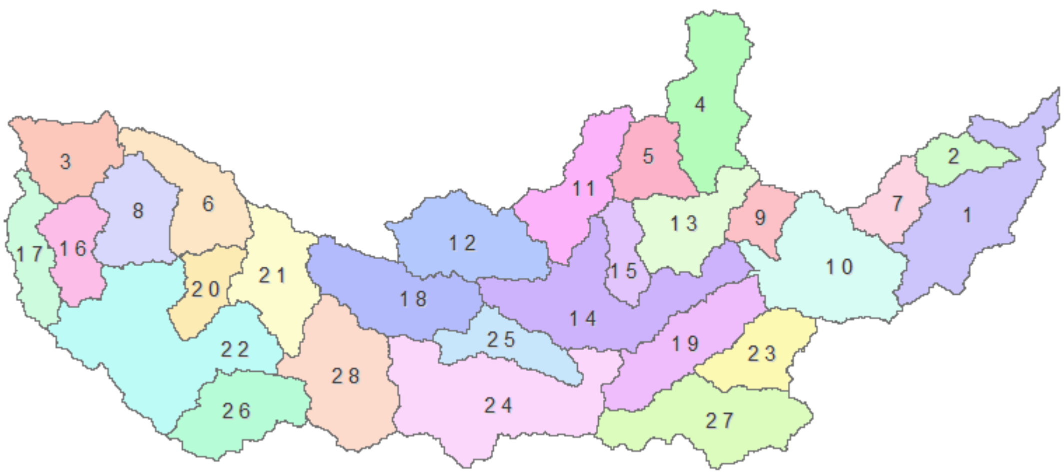


Figure 4.2: The Subbasins of the Wolf Creek Watershed

Because of computational constraints, for illustrative purpose, we run subsidy auctions at the subbasin level in the watershed rather than at the HRU level to meet different reliability targets. All 11 farm-management alternatives are considered in the auctions. Figure 4.2 displays all 28 subbasins in the Wolf Creek Watershed. In these auctions, every subbasin submits bids on all farm-management alternatives, and applies the same farm-management practices everywhere within the subbasin. When their bids on Rf, RC, RN, and RNC are accepted, they expect a fine/reward on them, which depends on the total pollution. For example, if Subbasin 1's bid on reduced fertilizer is accepted in a subsidy auction to meet a 30% reduction in the pollution with 70% reliability level, each HRU within this subbasin is subject to a fine of $338,000 and a reward of \$145,000 according to Table 4.3.

Table 4.5 displays the results of subsidy auctions at the subbasin level and the efficient farm-management practices to achieve different reliability targets. In the efficient solution, Pr and RC are widely used. Land retirement is effective and indispensable in achieving a reliable reduction in the pollution. More area is converted to prairie with a more stringent target. The total subsidy paid to farmers is higher than their total cost. The information rent, i.e. the difference between total subsidy and the total cost, exists to motivate every subbasin to disclose its actual cost. The information rent seems to increase slightly with a more stringent reliability target. The size of information rent is significant, and almost half of the total subsidy is paid for this information rent. However, there is no way to avoid it, without harming the cost-effectiveness of meeting a reliability target.

Table 4.5: Subsidy Auction to Meet Different Reliability Targets: 70% Reliability Requirement, Subbasin Level (\$Millions)

Reduction	X^*	π^*	**TC**	**TP**	**TP-TC**
30%	SUB1-11, 13, 16-20, 22: RC; Other: Pr	29.63	56.52	115.86	59.33
35%	SUB1-8, 10-13, 16-17, 20, 22: RC; Other: Pr	24.46	61.69	121.63	59.94
40%	SUB1, 3-8, 10-11, 16-17, 19-20, 22: RC; Other: Pr	19.20	66.95	128.51	61.56
45%	SUB1, 4-6, 8, 10-11, 16-17, 22: RC; SUB7: Cc; Other: Pr	13.83	72.32	135.49	63.17
50%	SUB1-6, 8, 10-11, 16-17, 20: RC; SUB7: Cc; Other: Pr	8.47	77.68	143.23	65.55

TC is the total abatement cost of the farmers in the watershed. TP is the total subsidy paid to the farmers in the watershed.

4.5 Conclusions

This paper discusses implementation under asymmetric information to achieve reliable reductions in nonpoint source pollution. Asymmetric information involves farmers' unobservable actions like fertilizer application and the private information on their profits. This paper develops a VCG-payoff subsidy auction that prompts farmers to disclose their private information, as truthful revelation is a dominant strategy for them. We also incorporate a fine/reward scheme into the auction. It settles the moral hazard problem caused by unobservable fertilizer application. By properly setting the values of the fine and the reward, farmers will opt in and use the proper amount of fertilizer to attain the reliability target of pollution control in a cost-effective way. This auction is proved to minimize total abatement cost of meeting a reliability target under asymmetric information.

There are opportunities for future work on pollution control under asymmetric information. In the paper, we assume that the reduced fertilizer $\boldsymbol{r}_{\boldsymbol{B}}^{*}$ in BMP is set at the minimum fertilizer application rate that farmers will consider in the area. This assumption helps prevent farmers from reducing fertilizer too much under a sufficiently high fine/reward. While relaxing this assumption does affect meeting a reliability target, it matters whether a reliability target is achieved in a cost-effective way. If it allows more flexibility in reduced fertilizer application, other performance-based instrument such as a tax/subsidy may work better than a fine/reward to motivate the proper use of fertilizer, but it is more information intensive. There will be other challenges in research on designing a proper performance-based instrument to prevent moral hazard, while maintaining truthful revelation as a dominant strategy for farmers in the auction mechanism. This performance-based instrument keeps the a VCG payoff structure, which achieves a disconnect between one's bid and one's payment, and makes it optimal for participants not to deviate from the effective solution to a pollution target.

Moreover, like the other VCG mechanism, this subsidy auction bears the budget-imbalance problem. Walker (1980) proves that it is impossible for a truthfully-telling mechanism to be budget-balanced. It is impossible to have budget constraints on bidders or subsidy payments, either (Ausubel and Milgrom, 2004). We also discussed the information rent, which is significant and unavoidable in this subsidy auction mechanism, because it prompts truthful disclose of private information. Lewis (1996) reveals that the optimal mechanism for decreasing information rent typically ask a price of productive efficiency of pollution control.

Chapter 5

Conclusion and Discussion

This dissertation focuses on issues of water pollution control from point sources and nonpoint sources. It analyzes the cost-effectiveness of water pollution control and addresses the objective of pollution control under environmental uncertainty. The three essays respectively examine permit trading of water pollution, the reliability of pollution control under environmental uncertainty, and the asymmetric information problem in pollution control. This dissertation contributes to improved water pollution control by considering the difference of environmental damage persistence when the environmental damage function is known, where there is a probability distribution of pollution under environmental uncertainty, and when asymmetric information is a feature of the problem.

The first essay examines the cost-effectiveness of permit trading among point polluters and incorporates diversity in the degree of environmental damage persistence into trading ratios. This modification of trading ratios takes account of the difference between flow pollution and stock pollution, which has been little mentioned in previous literature on permit trading. It therefore properly solves the non-uniform mixing problem in water quality trading, and assists achievement of cost-effective pollution control. With regard to a broader water system, multiple constraints may be imposed on the environmental damage caused by flow pollution and stock pollution. Proper trading ratios can also be developed to attain the cost-effective result of this pollution control problem, but complete information on polluters' abatement costs becomes necessary.

The second and the third essays address agricultural water pollution control under environmental uncertainty. The second essay emphasizes that the objective of pollution control under environmental uncertainty is to improve the entire probability distribution of pollution, rather than a pollution level in a specific scenario. Thus, it suggests the use of a reliability target, which caps the failure probability of meeting a pollution reduction goal. The empirical study of the Wolf Creek Watershed of Iowa shows that, by meeting a reliability target with a 41% nitrogen reduction and a 70% reliability requirement, this reduction goal could be met in nine out of ten years during 2004-2013 under environmental uncertainty. This reduction goal is achieved more consistently than that under an average target, i.e. five out of ten years.

With advances in biophysical models of soil and water, e.g. SWAT, reasonable estimations of the effect of different farm-management practices on agricultural water pollution can be obtained to support the analysis of agricultural water pollution control. This essay finds that different farm-management practices and their spatial allocation over the landscape have an impact the probability distribution of total pollution. A farmer's marginal contribution towards meeting a reliability target on total pollution depends not only on their own action but also on others' actions. Instead of having an effect on the expectation of total pollution, the effect of different farm-management practices on the probability distribution of total pollution should be considered so as to reach a reliability target.

Considering the asymmetric information problem in practice, the reliability of agricultural water pollution control is challenging to attain. The third essay solves the asymmetric information problem by developing a VCG-payoff auction and a penalty/reward scheme based on total pollution. In pollution control, especially nonpoint pollution control, asymmetric information comes from farmers' unobservable actions like fertilizer application, undetectable agricultural runoff from each of their farmland, and their private information on agricultural profits. By properly enforcing this VCG-payoff subsidy auction, farmers are prompted to truthfully disclose their private profit information. The penalty/reward scheme is imposed on the farmers who are subsidized to apply the unobservable practice, here fertilizer application. Under a proper rate of penalty/reward, farmers will find it optimal not to deviate from the proper fertilizer rate.

Overall, the results of this dissertation suggest improvement and modification of current water pollution control policies. First, a modification of the trading ratio in permit trading is necessary, and this will the difference in environmental damage persistence, so as to attain the cost-effective pollution control outcome. Second, the importance of the reliability of pollution control as well as the probability distribution of pollution should be emphasized in pollution control under environmental uncertainty. Although the current TMDL policy introduces a margin of safety to account for the reliability of pollution control, the value of this margin of safety is weakly determined, and there is no clear rule or guidance about how it connects with the reliability of pollution control. This dissertation reveals the relationship between a margin of safety and a reliability level of pollution control. It also suggests that in order to achieve a given level of reliability in pollution control, a constant margin of safety, which is commonly used currently, is not suitable. The level of a margin of safety should vary with the level of TMDL. This dissertation also points out the necessity of further research on the relationship between abatement practices and the probability distribution of pollution under environmental uncertainty.

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Appendix A

Chapter 2 Appendices

A.1 Cost-Effectiveness Problem for Stock Pollution Only

In the cost-effectiveness problem of stock pollution only, the Hamiltonian function H, the first order conditions and the transversality condition of this problem above are given below, where $\bar{\lambda}$ is a Lagrange multiplier constant over time:

$$H = \sum_{i=1}^{n} C_i(a_i) + \bar{\lambda}\left(\delta S - \frac{\bar{D}_S}{r}\right) + \mu\left(-\gamma S + \sum_{i=1}^{n} \tau_{is}\left(e_i^0 - a_i\right)\right),$$

$$C_i^{'}(a_i) - \mu\tau_{is} = 0, \quad \forall i \in \{1, 2, ..., n\},$$

$$\dot{\mu} - r\mu = \mu\gamma - \bar{\lambda}\delta,$$

$$\dot{S} = -\gamma S + \sum_{i=1}^{n} \tau_{is}\left(e_i^0 - a_i\right),$$

$$\lim_{t\to\infty} \mathrm{e}^{-rt} S(t)\mu(t) = 0.$$

Solving the differential equations, we have $\mu = \bar{\lambda}\delta/\left(r + \gamma\right)$, which is constant over time. The size of $\bar{\lambda}$ depends on $\bar{D}_S$. The damage constraint on stock pollution is always binding unless $\bar{D}_S$ is not stringent enough.

A.2 The Kuhn-Tucker Conditions of Problem (D)

Every polluter attempts to minimize its abatement cost and the cost incurred under permit trading. The Lagrange function of Problem (D) is:

$$L_i = C_i(a_i) - p_i r_{si} + \sum_{j \neq i} p_j r_{ji} + \lambda_i \left[\left(e_i^0 - r_{ki}\right) - \sum_{j \neq i} t_{ji} r_{ji} \right].$$

The Kuhn-Tucker Conditions are:

$$\begin{aligned}
&r_{ki} : C_i^{'}(a_i) - \lambda_i \geq 0, \quad r_{ki} \geq 0, \quad \left(C_i^{'}(a_i) - \lambda_i\right) r_{ki} = 0, \\
&r_{si} : C_i^{'}(a_i) - p_i \geq 0, \quad r_{si} \geq 0, \quad \left(C_i^{'}(a_i) - p_i\right) r_{si} = 0, \\
&r_{ji} : p_j - \lambda_i t_{ji} \geq 0, \quad r_{ji} \geq 0, \quad \left(p_j - \lambda_i t_{ji}\right) r_{ji} = 0, \forall j \neq i, \\
&\lambda_i : \left(e_i^0 - r_{ki}\right) - \sum_j t_{ji} r_{ji} \leq 0, \lambda_i \geq 0, \left(\left(e_i^0 - r_{ki}\right) - \sum_j t_{ji} r_{ji} \right) \lambda_i = 0.
\end{aligned}$$

If the constraint λ_i is not binding, i.e. $\left(e_i^0 - r_{ki}\right) - \sum_j t_{ji} r_{ji} < 0$, λ_i will be zero. However, $\lambda_i = 0$ indicates either $p_j = 0$ or $r_{ji} = 0$ for any $j \neq i$. No market exists in this scenario. If the constraint λ_i is binding, i.e. $\left(e_i^0 - r_{ki}\right) - \sum_j t_{ji} r_{ji} = 0$, λ_i could be positive, $C_i^{'}(a_i) - \lambda_i = 0$, $C_i^{'}(a_i) - p_i = 0$, and $p_j - \lambda_i t_{ji} = 0$ due to non-arbitrage condition.[1]

A.3 The Permit Endowment in WQT, Both Flow Pollution and Stock Pollution

Each polluter in the permit market must meet the requirement that he cannot discharge more than what is allowed by the permits he possesses. That is,

$$\left(e_i^0 - r_{ki}\right) - \sum_{j \neq i} t_{ji} r_{ji} \leq 0, \quad \forall i \in \{1, 2, ..., n\}.$$

Because $r_{si} + r_{ki} = \bar{l}_i + a_i$, the above inequality is rearranged as follows:

$$\left(e_i^0 - a_i\right) \leq \bar{l}_i - r_{si} + \sum_{j \neq i} t_{ji} r_{ji}, \quad \forall i \in \{1, 2, ..., n\}$$

[1] If $C_i^{'}(a_i) - \lambda_i = 0$ and $C_i^{'}(a_i) - p_i = 0$, then $p_j - \lambda_i t_{ji} = 0$. See the details in Konishi et al. (2015).

Multiplying both sides by the river damage coefficient d_i, aggregating over all polluters and discounting over time, we obtain the following inequality for environmental damage of flow pollution:

$$\int_0^{+\infty}\sum_{i=1}^n d_i\left(e_i^0-a_i\right)\mathrm{e}^{-rt}\mathrm{d}t \leq \int_0^{+\infty}\sum_{i=1}^n d_i\left(\bar{l}_i-r_{si}+\sum_{j\neq i}t_{ji}r_{ji}\right)\mathrm{e}^{-rt}\mathrm{d}t. \tag{A.1}$$

According to the state equation $\dot{S}=-\gamma S+\sum_{i=1}^n \tau_{is}(e_i^0-a_i)$, the discounted environmental damage of stock pollution is:

$$\begin{aligned}\int_0^{+\infty}\delta S\mathrm{e}^{-rt}\mathrm{d}t=&\int_0^{+\infty}\delta\left[\left(S_0-\frac{1}{\gamma}\sum_{i=1}^n\tau_{is}\left(e_i^0-a_i\right)\right)\mathrm{e}^{-\gamma t}+\frac{1}{\gamma}\sum_{i=1}^n\tau_{is}\left(e_i^0-a_i\right)\right]\mathrm{e}^{-rt}\mathrm{d}t\\ =&\frac{\delta S_0}{r+\gamma}+\frac{\delta}{r(r+\gamma)}\sum_{i=1}^n\tau_{is}\left(e_i^0-a_i\right)\\ \leq&\frac{\delta S_0}{r+\gamma}+\frac{\delta}{r(r+\gamma)}\sum_{i=1}^n\tau_{is}\left(\bar{l}_i-r_{si}+\sum_{j\neq i}t_{ji}r_{ji}\right).\end{aligned} \tag{A.2}$$

Combining inequalities (A.1) and (A.2), we have the following inequality describing the discounted environmental damage of both flow pollution and stock pollution:

$$\begin{aligned}&\int_0^{+\infty}\sum_{i=1}^n d_i\left(e_i^0-a_i\right)\mathrm{e}^{-rt}\mathrm{d}t+\int_0^{+\infty}\delta S\mathrm{e}^{-rt}\mathrm{d}t\\ \leq&\int_0^{+\infty}\sum_{i=1}^n d_i\left(\bar{l}_i-r_{si}+\sum_{j\neq i}t_{ji}r_{ji}\right)\mathrm{e}^{-rt}\mathrm{d}t+\frac{\delta S_0}{r+\gamma}+\frac{\delta}{r(r+\gamma)}\sum_{i=1}^n\tau_{is}\left(\bar{l}_i-r_{si}+\sum_{j\neq i}t_{ji}r_{ji}\right)\\ =&\frac{1}{r}\sum_{i=1}^n\left(d_i+\frac{\delta\tau_{is}}{r+\gamma}\right)\bar{l}_i-\frac{1}{r}\sum_{i=1}^n\left(d_i+\frac{\delta\tau_{is}}{r+\gamma}\right)\left(r_{si}-\sum_{j\neq i}t_{ji}r_{ji}\right)+\frac{\delta S_0}{r+\gamma}.\end{aligned}$$

In the equilibrium of permit trading, if permit prices are nonzero, we have $r_{sj}=\sum_{i\neq j}r_{ji}$, $\forall j\in\{1,2,...,n\}$. Given the cost-effective trading ratio $t_{ij}=C_i'(a_i^*)/C_j'(a_j^*)$, we have:

$$
\begin{aligned}
&\frac{1}{r}\sum_{i=1}^{n}\left(d_i+\frac{\delta\tau_{is}}{r+\gamma}\right)\left(r_{si}-\sum_{j\neq i}t_{ji}r_{ji}\right)\\
=&\frac{1}{r}\left(\sum_{i=1}^{n}\left(d_i+\frac{\delta\tau_{is}}{r+\gamma}\right)r_{si}-\sum_{i=1}^{n}\sum_{j\neq i}\left(d_i+\frac{\delta\tau_{is}}{r+\gamma}\right)t_{ji}r_{ji}\right)\\
=&\frac{1}{r}\left(\sum_{j=1}^{n}\left(d_j+\frac{\delta\tau_{js}}{r+\gamma}\right)r_{sj}-\sum_{j=1}^{n}\sum_{i\neq j}\left(d_i+\frac{\delta\tau_{is}}{r+\gamma}\right)t_{ji}r_{ji}\right)\\
=&\frac{1}{r}\sum_{j=1}^{n}\left(d_j+\frac{\delta\tau_{js}}{r+\gamma}\right)\left(r_{sj}-\sum_{i\neq j}r_{ji}\right)\\
=&\,0.
\end{aligned}
$$

Since $\bar{D}$ is the limit on the discounted total damage, there is $\int_0^{+\infty}\sum_{i=1}^{n}d_i\left(e_i^0-a_i\right)\mathrm{e}^{-rt}\mathrm{d}t+\int_0^{+\infty}\delta S\mathrm{e}^{-rt}\mathrm{d}t\leq\bar{D}$. Therefore, to achieve the cost-effective result of pollution control with a limit $\bar{D}$, the amount of permits in WQT shall be:

$$
\sum_{i=1}^{n}\left(d_i+\frac{\delta}{r+\gamma}\tau_{is}\right)\bar{l}_i\leq\left(\bar{D}-\frac{\delta S_0}{r+\gamma}\right)r.
$$

A.4 The Cost Difference between No-persistence Market and All-Inclusive Market

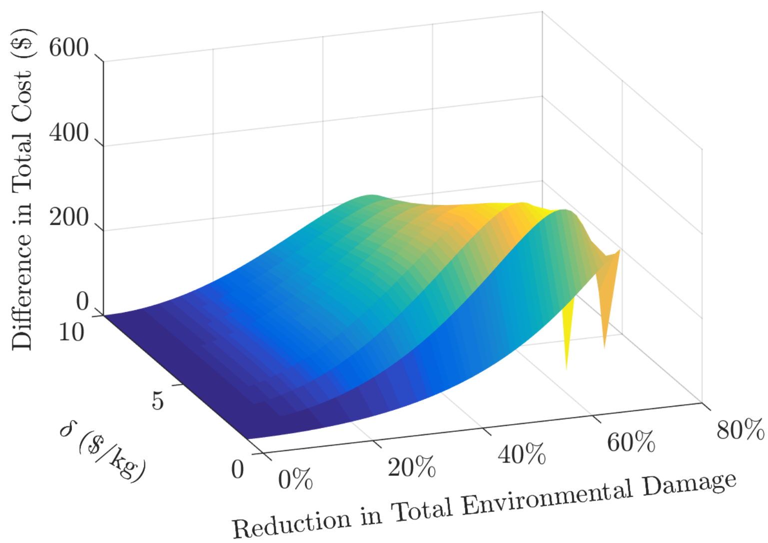

Figure A.1: The Cost Difference between No-persistence Market and All-Inclusive Market: δ

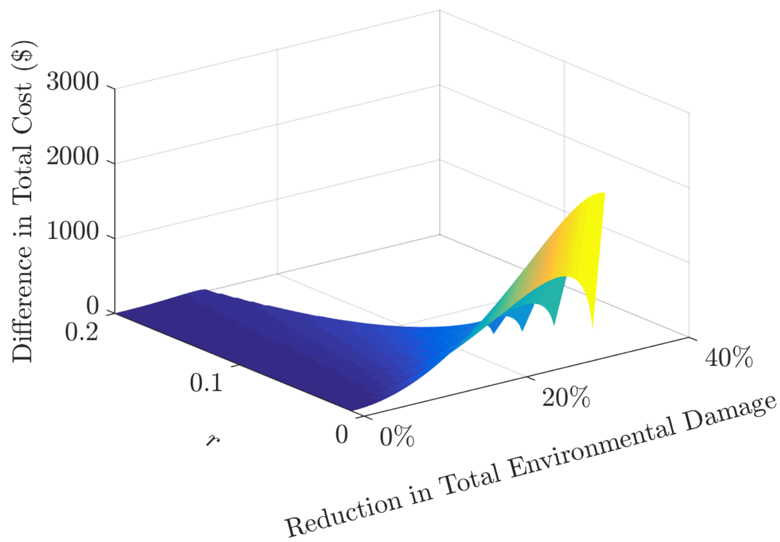

Figure A.2: The Cost Difference between No-persistence Market and All-Inclusive Market: r

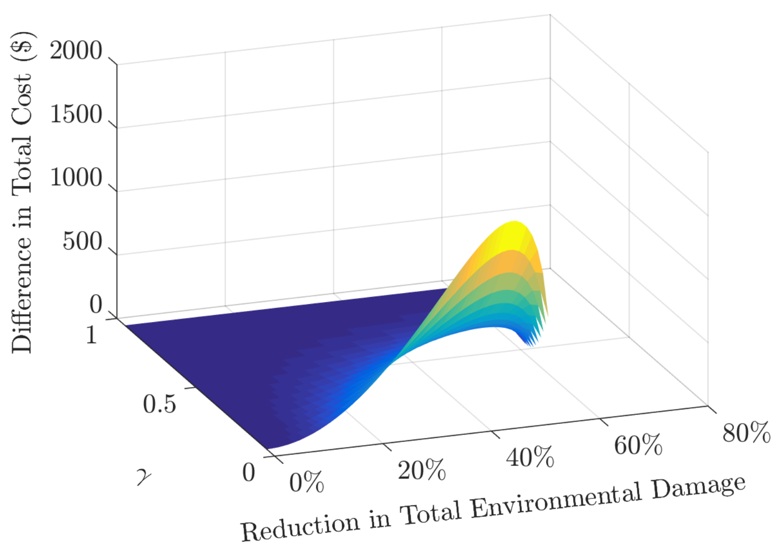

Figure A.3: The Cost Difference between No-persistence Market and All-Inclusive Market: γ

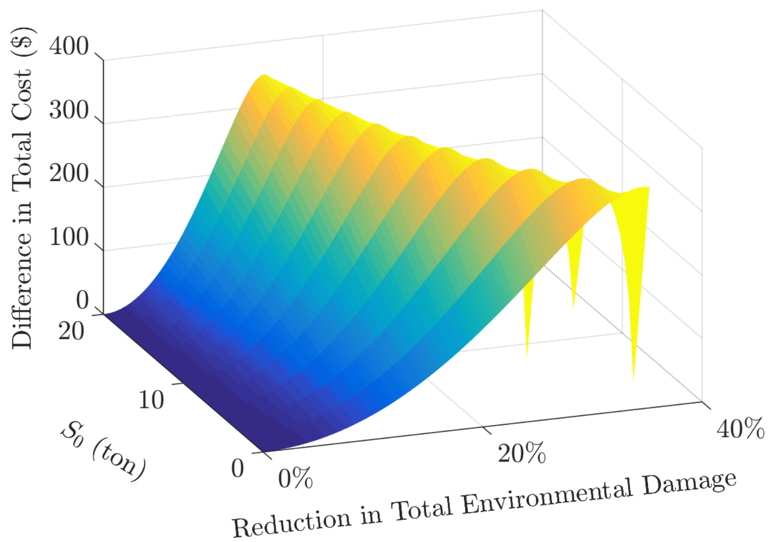

Figure A.4: The Cost Difference between No-persistence Market and All-Inclusive Market: S_0

Appendix B

Chapter 3 Appendices

B.1 Two Versions of Chebyshev's Inequality

Cantelli's Inequality (The One-sided Chebyshev's Inequality)

Let $y = R(\boldsymbol{X};\boldsymbol{\epsilon}) - \mu(\boldsymbol{X};\boldsymbol{\epsilon})$, then the mean of y is $\mu_y = 0$ and the variance of y is $\sigma_y^2 = \sigma^2(\boldsymbol{X};\boldsymbol{\epsilon})$. For any $t \in \mathbb{R}$ and $\delta > 0$ such that $t + \delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon}) > 0$, we have

$$\begin{aligned}
\mathbb{P}\left(y \geq \delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})\right) &= \mathbb{P}\left(y + t \geq t + \delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})\right) \\
&= \mathbb{P}\left(\frac{y+t}{t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})} \geq 1\right) \\
&= \mathbb{P}\left(\left(\frac{y+t}{t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})}\right)^2 \geq 1\right).
\end{aligned}$$

By the Markov inequality:

$$\begin{aligned}
\mathbb{P}\left(\left(\frac{y+t}{t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})}\right)^2 \geq 1\right) &\leq \mathbb{E}\left(\left(\frac{y+t}{t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})}\right)^2\right) \\
&= \mathbb{E}\left(\left(\frac{y}{t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})}\right)^2\right) + \left(\frac{t}{t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon})}\right)^2 \\
&= \frac{\sigma^2(\boldsymbol{X};\boldsymbol{\epsilon}) + t^2}{(t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon}))^2}.
\end{aligned}$$

Since $t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon}) > 0$, to minimize the value above we obtain $t^* = \dfrac{\sigma(\boldsymbol{X};\boldsymbol{\epsilon})}{\delta}$. Therefore,

$\dfrac{\sigma^2(\boldsymbol{X};\boldsymbol{\epsilon})+t^2}{(t+\delta\sigma(\boldsymbol{X};\boldsymbol{\epsilon}))^2} \leq \dfrac{1}{1+\delta^2}$. In this sense,

$$\mathbb{P}\left(\frac{R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})}{\sigma(\boldsymbol{X};\boldsymbol{\epsilon})} \geq \delta\right) \leq \frac{1}{1+\delta^2}.$$

The Semivariance Inequality

According to the definition of semivariance:

$$\begin{aligned}\hat{\sigma}^2(\boldsymbol{X};\boldsymbol{\epsilon}) \quad = \quad & \int_{\mu(\boldsymbol{X};\boldsymbol{\epsilon})}^{\mu(\boldsymbol{X};\boldsymbol{\epsilon})+\delta\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})} \left(R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})\right)^2 \mathrm{d}F(R) \\ & + \int_{\mu(\boldsymbol{X};\boldsymbol{\epsilon})+\delta\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})}^{+\infty} \left(R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})\right)^2 \mathrm{d}F(R).\end{aligned}$$

Therefore,

$$\int_{\mu(\boldsymbol{X};\boldsymbol{\epsilon})+\delta\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})}^{+\infty} \left(R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})\right)^2 \mathrm{d}F(R) < \hat{\sigma}^2(\boldsymbol{X};\boldsymbol{\epsilon}).$$

According to the definition of an integral, it has

$$\int_{\mu(\boldsymbol{X};\boldsymbol{\epsilon})+\delta\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})}^{+\infty} \left(R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})\right)^2 \mathrm{d}F(R) > \delta^2\hat{\sigma}^2(\boldsymbol{X};\boldsymbol{\epsilon}) \int_{\mu(\boldsymbol{X};\boldsymbol{\epsilon})+\delta\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})}^{+\infty} \mathrm{d}F(R),$$

$$\text{and} \quad \int_{\mu(\boldsymbol{X};\boldsymbol{\epsilon})+\delta\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})}^{+\infty} \mathrm{d}F(R) = \mathbb{P}\left(\frac{R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})}{\sigma(\boldsymbol{X};\boldsymbol{\epsilon})} \geq \delta\right).$$

We conclude that

$$\mathbb{P}\left(\frac{R(\boldsymbol{X};\boldsymbol{\epsilon})-\mu(\boldsymbol{X};\boldsymbol{\epsilon})}{\hat{\sigma}(\boldsymbol{X};\boldsymbol{\epsilon})} \geq \delta\right) \leq \frac{1}{\delta^2}.$$

B.2 Model Setup in the Empirical Application

In the empirical study of the Wolf Creek Watershed, the optimization model used in the programming is:

$$
\begin{aligned}
&\max_{\boldsymbol{X}} \frac{1}{10} \sum_{t=1}^{10} \pi_t \left(\boldsymbol{X}; \boldsymbol{\epsilon}\right), \\
&\text{s.t.} \quad \mathbb{P}\left(R(\boldsymbol{X}; \boldsymbol{\epsilon}) \geq \bar{R}\right) \leq \alpha, \\
&\sum_{j=1}^{14} x_{ij} = 1, \quad \forall i, \\
&x_{ij} \in \{0, 1\}, \quad \forall i, \forall j, \\
&\pi_t(\boldsymbol{X}; \boldsymbol{\epsilon}) = \sum_{i=1}^{7528} \left(\boldsymbol{p}\boldsymbol{y_{i,t}}(\boldsymbol{x_i}; \boldsymbol{\epsilon}) - \boldsymbol{c_i}\boldsymbol{x_i}\right).
\end{aligned}
\tag{B.1}
$$

The chance constraint can be converted into the following to derive a robust solution:

$$
\begin{aligned}
&\min\left(\mu(\boldsymbol{X}; \boldsymbol{\epsilon}) + \sqrt{\frac{1}{\alpha} - 1}\ \sigma(\boldsymbol{X}; \boldsymbol{\epsilon}), \quad \mu(\boldsymbol{X}; \boldsymbol{\epsilon}) + \sqrt{\frac{1}{\alpha}}\ \hat{\sigma}(\boldsymbol{X}; \boldsymbol{\epsilon})\right) \leq \bar{R} \\
&\text{where } \mu(\boldsymbol{X}; \boldsymbol{\epsilon}) = \frac{1}{10} \sum_{t=1}^{10} \sum_{i=1}^{7528} R_{i,t}(\boldsymbol{x_i}; \boldsymbol{\epsilon}), \\
&\sigma^2(\boldsymbol{X}; \boldsymbol{\epsilon}) = \frac{1}{9} \sum_{t=1}^{10} \left(\sum_{i=1}^{7528} R_{i,t}(\boldsymbol{x_i}; \boldsymbol{\epsilon}) - \mu(\boldsymbol{X}; \boldsymbol{\epsilon})\right)^2, \\
&\hat{\sigma}^2(\boldsymbol{X}; \boldsymbol{\epsilon}) = \frac{1}{9} \sum_{t=1}^{10} \mathbb{1}\left(\sum_{i=1}^{7528} R_{i,t}(\boldsymbol{x_i}; \boldsymbol{\epsilon}) > \mu(\boldsymbol{X}; \boldsymbol{\epsilon})\right) \left(\sum_{i=1}^{7528} R_{i,t}(\boldsymbol{x_i}; \boldsymbol{\epsilon}) - \mu(\boldsymbol{X}; \boldsymbol{\epsilon})\right)^2.
\end{aligned}
\tag{B.2}
$$

The crop production $\boldsymbol{y_{i,t}}$ and the total nitrogen runoff $R_{i,t}$ of each farmer in each year are available in the SWAT results. This problem can be transformed into a mixed-integer second-order cone programming problem (MISOCP), and solved by the interior point method and the branch and bound method. The corresponding cost-effective solution takes into account both environmental uncertainty and spatial heterogeneity.

B.3 Crop Management Schedule

The following displays the crop management schedule for corn-soybean rotation in the Wolf Creek Watershed, which grows corn in the first year. The schedule for soybean-corn rotation just swaps year.[1]

Year 1

May 1st	Spring tillage: field cultivator
May 4th	Plant corn
May 5th	Fertilizer
Oct 21st	Harvest corn
Oct 28th	Fall tillage: chisel plow

Year 2

May 12th	Spring tillage: field cultivator
May 18th	Plant soybean
Oct 7th	Harvest soybean
Oct 14th	Fall tillage: chisel plow

B.4 Farm Management Alternatives

Status Quo Baseline (Ba): This is based on the 2008 Crop Data Layer. The crop management has been applied to the cropland.

All Crop (Ac): The crop management has been applied to all HRUs that are not in the “Transportation-Roads” (Road) class. Where appropriate, model curve number values have been changed to reflect the transition from: Range to Crop, Forest to Crop, and Wetlands to Crop. Range to Crop: increase Cn2 by 10%, Forest to Crop: increase Cn2 by 15%, Wetlands to Crop: increase Cn2 by 15%.

Conservation Tillage (Ct): This is the same as Ac except that Fall tillage operations have been switched from chisel plow to a generic conservation tillage practice. Model curve numbers have been updated to reflect the change in tillage practice. For all HRUs except Road class, decrease Cn2 by 4%. Moreover, conservation tillage can also be called low-tillage but not strip-tillage.

No Tillage (Nt): This is the same as Ct except that the field cultivator has been replaced with generic no-till mixing in Spring, and generic conservation tillage has been replaced with generic no-till mixing in Fall. SCS Curve number is decreased to reflect

[1] This content is adopted from Brent Dalzell’s notes on SWAT simulation.

additional crop residue on the soil surface. Cn2 has been decreased by 4% for all HRUs except for Road class. Biological mixing increased from 0.2 to 0.4 to reflect expected increase in soil biological activity in the absence of tillage disturbance.

Grassed Waterways (Gw): This is the same as Ac except that grassed waterways have been implemented for all HRUs except for Road class. Grassed waterway width has been set to 10m. Other model parameters are based on HRU characteristics (model default). Mannings roughness coefficient is 0.35 and Specific Conductivity is set to 0.005. In Operations Scheduling, add Operation of Grassed Waterway. In all, the related parameters are GWATI = 1, GWATN = 0.35, GWATL = 0, GWATW = 10, GWATD =0, GWATS = 0, GWATSPCON = 0.005.

Reduced Fertilizer (Rf): This is the same as Ac except that the nitrogen application rate has been reduced by 10%, i.e., to 145 kg/ha, and phosphorus application rate has been reduced by 17%, i.e., to 20.75 kg/ha.

Cover Crop (Cc): This is the same as Ac except that rye is grown between corn and soybeans. When it is corn going into soybean, rye is planted (Oct 29th) immediately following corn harvest and Fall tillage. It is killed (May 11th) immediately before soybean Spring tillage. When it is soybean going into corn, Winter Wheat is planted on October 15th and killed on May 2nd.

Prairie (Pr): All HRUs that are not in the Road class have been switched to the "Range-Grasses" class. Where appropriate, model curve number values have been changed to reflect the transition from: Crop to Grass, Forest to Grass, and Wetlands to Grass. Crop to Prairie: decrease Cn2 by 10%, Forest to Prairie: increase Cn2 by 5%, Wetlands to Prairie: increase Cn2 by 5%. For all HRUs, ESCO is set 0.9. Prairie scenarios are calibrated for plant phenology and biomass from available datasets and primary literature. No assumptions are made about specific mixtures of grasses. It is assumed that grasslands are established with no seeding operations or machinery involved.

Forest (Fd): All HRUs that are not in the Road class have been switched to the "Forest-Deciduous" class. Where appropriate, model curve number values have been changed to reflect the transition from: Crop to Forest and from Range-Grasses to Forest. Cn2 decreased by 5% relative to values established for the Prairie Scenario.

Reduced Fertilizer and No Tillage (RN): This is the same as Rf except that the field cultivator has been replaced with generic no-till mixing in Spring, and Tillage has been replaced with generic no-till mixing in Fall. SCS Curve number is decreased to reflect additional crop residue on the soil surface. Cn2 decreased by 8% for all HRUs except for Urban/Transportation. Biological mixing increased from 0.2 to 0.4 to reflect expected increase in soil biological activity in the absence of tillage disturbance.

Reduced Fertilizer and Cover Crop (RC): This is the same as Rf except that cover crop is grown between corn and soybeans. When it is corn going into soybeans, rye is planted (Oct 29th) immediately following corn Harvest and Fall tillage. The cover crop is terminated (May 11th) immediately before soybean Spring tillage. When it is soybean going into corn, rye is planted on October 15th and killed on May 2nd.

No Tillage and Cover Crop (NC): This is the same as Cc except that field cultivator has been replaced with generic no-till mixing in Spring, and tillage has been replaced with generic no-till mixing in Fall. The SCS Curve number is decreased to reflect additional crop residue on the soil surface. Cn2 has been decreased by 8% for all HRUs except for Road class. Biological mixing increased from 0.2 to 0.4 to reflect expected increase in soil biological activity in the absence of tillage disturbance.

Reduced Fertilizer, No Tillage and Cover Crop (RNC): This is the same as RC except that field cultivator has been replaced with generic no-till mixing in Spring, and Tillage has been replaced with generic no-till mixing in Fall. The SCS Curve number is decreased to reflect additional crop residue on the soil surface. Cn2 has been decreased by 8% for all HRUs except for Road class. Biological mixing increased from 0.2 to 0.4 to reflect expected increase in soil biological activity in the absence of tillage disturbance.

B.5 Crop Enterprises

Part of BMP cost is included in the preharvest machinery cost of the crop enterprise for each farm management alternative.

Table B.1: Estimated Preharvest Machinery Cost

Farm Management	Corn Following Soybean	Soybean Following Corn
Ba, Ac, Rf	Field cultivator	Field cultivator
	Sprayer	Sprayer (2x)
	Tandem disk	Tandem disk
	Planter	Planter
	NH3 applicator	Chisel plow
	Chisel plow	
Ct	Field cultivator	Tandem Disk
	Sprayer	Sprayer (2x)
	Planter	Grain drill
	NH3 applicator	Conservation tillage
	Conservation tillage	
Nt, RN	Sprayer	Sprayer (2x)
	Tandem disk	Tandem disk
	NH3 applicator	No-till planter, soybean
	No-till planter, corn	Pestcide-burn down
	Pestcide-burn down	Save seedbed preparation
	Save seedbed preparation	
Cc, RC	Field cultivator	Field cultivator
	Sprayer	Sprayer (2x)
	Tandem disk	Tandem disk
	Planter	Planter
	NH3 applicator	Chisel plow
	Chisel plow	Cover crop
	Cover crop	

Table B.2: Estimated Preharvest Machinery Cost (Continued)

Farm Management	Corn Following Soybean	Soybean Following Corn
Gw	Field cultivator	Field cultivator
	Sprayer	Sprayer (2x)
	Tandem disk	Tandem disk
	Planter	Planter
	NH3 applicator	Chisel plow
	Chisel plow	Grassed waterway
	Grassed waterway	
NC, RNC	Sprayer	Sprayer (2x)
	Tandem disk	Tandem disk
	NH3 applicator	No-till planter, soybean
	No-till planter, corn	Pestcide-burn down
	Pestcide-burn down	Save seedbed preparation
	Save seedbed preparation	Cover crop
	Cover crop	

In the following, I provide the crop enterprise under the status quo baseline in year 2015. The crop enterprises under the other 12 alternatives of farm management are obtained in a similar way with proper changes in different cost items. The final cost of each farm management practice is the average production cost of corn and soybean from 2011 to 2015, adjusted for inflation.

Table B.3: Estimated Crop Production Cost on Corn Following Soybean

			Fixed	**Variable**
Preharvest Machinery		22.70	24.00	
Seed, Chemical, etc		**Price per unit**	**Units**	
	Seed	0.00386	25,000	96.50
	Nitrogen	0.47	143.64	67.51
	Phosphate	0.48	51.04	24.50
	Potash	0.41	48.00	19.68
	Lime			10.00
	Herbicide			35.50
	Crop insurance			12.20
	Miscellaneous			9.00
	Interest			9.96
Harvest Machinery				
	Combine		19.00	10.90
	Grain cart		5.90	3.20
	Haul		6.52	6.11
	Dry		8.00	30.72
	Handle (auger)		2.63	3.51
Labor		33.80		
Total per acre			98.55	363.29

Table B.4: Estimated Crop Production Cost on Soybean Following Corn

			Fixed	Variable
Preharvest Machinery			20.00	20.60
Seed, Chemical, etc		**Price per unit**	**Units**	
	Seed	0.39	140	55.00
	Phosphate	0.48	51.04	24.50
	Potash	0.41	75.00	30.75
	Lime			10.00
	Herbicide			26.50
	Crop insurance			8.90
	Miscellaneous			10.00
	Interest			6.21
Harvest Machinery				
	Combine		15.20	8.40
	Grain cart		5.90	3.20
	Haul		2.04	1.91
	Handle (auger)		0.82	1.10
Labor			29.25	
Total per acre			73.21	207.07

B.6 The Margins of Safety in EPA Region 5 and 7

Table B.5: Margins of Safety in TMDL Projects in EPA Region 5 and 7

MOS	Project	Description
10%	Yellow River Basin, Iowa	MOS is an explicit 10% of TMDL of *Escherichia Coli*.
10%	Mud Creek, Iowa	MOS is an explicit 10% of TMDL of *Escherichia Coli*.
15%	Cedar River Watershed, Iowa	MOS is an explicit 15% if TMDL of indicator bacteria impairment.
10%	Prairie Dog Creek, Kansas	MOS is an explicit 10% TMDL of total phosphorus and total nitrogen.
10%	Norton Lake, Kansas	MOS is an explicit 10% TMDL of total phosphorus, total nitrogen, and total suspended solids.
10%	Pomona Lake, Kansas	MOS is an explicit 10% TMDL of total phosphorus and total nitrogen.
10%	Village Creek, Missouri	MOS is an explicit 10% TMDL of sediments.
10%	Shibboleth Creek, Missouri	MOS is an explicit 10% TMDL of sediments.
10%	Pond Creek watershed, Missouri	MOS is an explicit 10% TMDL of sediments.
10%	Elkhorn Basin, Nebraska	MOS is an explicit 10% of TMDL of *Escherichia Coli*.

Table B.6: Margins of Safety in TMDL Projects in EPA Region 5 and 7 (Continued)

MOS	Project	Description
10%	Papillion Creek Watershed, Nebraska	MOS is an explicit 10% of TMDL of *Escherichia Coli*.
10%	Twin Cities Metro Area, Minnesota	MOS is an explicit 15% if TMDL of Chloride.
$35.0\% \sim 66.5\%$	Redwood River, Minnesota	MOS is an explicit portion of TMDL of fecal coliform and turbidty impairments. It changes with flows.
$36.0\% \sim 94\%$	Cottonwood River, Minnesota	MOS is an explicit portion of TMDL of fecal coliform and turbidty impairments. It changes with flows.
10%	Skillet Fork Watershed, Illinois	MOS is an explicit 10% TMDL of total phosphorus.
10%	Mt. Olive New Lake, Mt. Olive Old Lake and Staunton Lake Watersheds, Illinois	MOS is an explicit 10% TMDL of total phosphorus and Manganese.
5%	Southern Whitewater River Watershed, Indiana	MOS is an explicit 5% of TMDL of *Escherichia Coli*, nutrient, and total suspended solids.
$20\% \sim 52\%$	Rouge River, Michigan	MOS is an explicit portion of TMDL of *Escherichia Coli*. It changes with flows.
5%	Mead Lake, Wisconsin	MOS is an explicit 5% TMDL of total phosphorus.

Table B.7: Margins of Safety in TMDL Projects in EPA Region 5 and 7 (Continued)

MOS	Project	Description
20%	Lower Sandusky River and Sandusky Bay Watershed, Ohio	MOS is an explicit 20% of TMDL of *Escherichia Coli*.
10%	Squaw Creek and Stillwell Creek, Wisconsin	MOS is an explicit 10% TMDL of sediments.
$9\% \sim 32\%$	Otter Creek, Wisconsin	MOS is an explicit portion of TMDL of total suspended solids. It changes with flows.

Appendix C

Chapter 3 Appendices

C.1 Proof: r^*_{Bi} is the optimal solution in Problem (4.3)

Denote the objective function of Problem (4.3) as L. Given that $\mathbb{E}(\pi'_{r_i}) > 0$, $F'_{r_i}(\bar{R}) < 0$ and sufficiently high g and q, its first derivative is:

$$\frac{\partial L}{\partial r_i} = \frac{\partial \mathbb{E}\left(\pi_i\left((\boldsymbol{b^*_{Bi}}, r_i), \boldsymbol{\epsilon}\right)\right)}{\partial r_i} + \frac{\partial F(\bar{R})}{\partial r_i}(g+q) \leq 0.$$

Since $\boldsymbol{r^*_B}$ is the lowest fertilizer application rate of farmers, there is $L(r^*_{Bi}) \geq L(r_i)$. The optimal solution of farmers to Problem (4.3) is r^*_{Bi}, and the optimal objective value is $\mathbb{E}\left(\pi_i\left(\boldsymbol{x^*_{Bi}}, \boldsymbol{\epsilon}\right)\right)$.